ESSAYS ON ECO-INNOVATION AND FIRM PERFORMANCE IN FRANCE

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Abstract

To mitigate environmental concerns and fight against climate change, eco-innovation provides an opportunity to establish France's leading role to overcome sustainability challenges. In this thesis, we investigate different aspects of eco-innovation focusing on French manufacturing firms. Firstly, We examine how collaboration between firms affects the decision of firms that currently undertake R&D to take the next step and also invest in increasingly complex environmental or eco-innovation. Our results show that R&D collaboration is essential in stimulating eco-innovation. Secondly, we examine whether stringent environmental regulations harm firm competitiveness and further whether regulatory induced eco-innovation could offset environmental abatement pressure. Our results suggest that regulations harm business competitiveness and the intermediate effect of eco-innovation is not effective. Finally, we investigate whether firms investing in eco-innovation meet their environmental targets and remain competitive and more specifically, whether eco-innovation helps firms to improve their environmental performance. Results suggest that eco-innovation does not exhibit a significant effect on environmental performance for French manufacturing firms. Overall, this thesis emphasizes the lack of effectiveness of eco-innovation in France, we hope that this thesis can shed some light on the direction of further research.

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Introduction

Over the last two decades, the relationship between economic growth and environmental degradation has received considerable attention from academics and policymakers. In 2010, the European Commission set up a target strategy for smart, sustainable and inclusive economic growth for the European Union (EU) in the Europe 2020 Strategy (Commission, 2010). Along with economic growth, the environmental impacts associated with economic activities contribute greatly to climate change. To fight against climate change, the European Commission approved the 2030 climate and energy package in 2014 by which all EU member states committed to a 40% reduction in greenhouse gas emissions compared to 1990 levels, a 32% share of energy from renewable sources, and a 32.5% increase in energy efficiency (The European Commission, 2014). Decoupling environmental pressure from economic growth can be achieved through technological improvements which reduce environmental pressure (Popp et al., 2010). Technological improvement in improving environmental sustainability could also reduce the cost of meeting environmental requirements. Such technological change is often referred as eco-innovation.

The EU is devoting increasing resources to eco-innovation which is recognised as a key to improving the EU's strategic position in the global market. Being the third largest economy in the EU, France is one of the key participants in the field of environmental protection. France has a significantly low-carbon energy mix, due to the dominant position of electricity in total energy consumption and the key role of nuclear energy in electricity generation. According to RTE (2019), 72.3% of total electricity production comes from nuclear power in 2016. Due to the unique energy structure, France benefit from the lowest CO_2 emission per capita in the EU. However, as a highly industrialized country, France relies heavily on imported energy sources including natural gas and fuel to satisfy its energy consumption. Bank (2019) reports that the share of energy imported in total energy consumption in 2015 was approximately 45% and it leads to the fact that although the level of greenhouse gas (GHG) emissions has been decreasing, the total carbon footprint caused by the French population is not declining. To achieve the emissions reduction target set by 2030 climate and energy package, eco-innovation which is known as a crucial driver of successful transition towards sustainable development seems to provide a feasible tool.

Innovativeness is one of the fundamental instruments of growth strategies to enter new markets, to increase the existing market share and to provide the company with a competitive advantage. Schumpeter and Backhaus (2003) distinguish different types of innovation: new products, new methods of production, new sources of supply, the exploitation of new markets and new ways to organize business. Furthermore, innovation is not only related to products and processes, but also related to marketing and organization. As the primary international basis of guidelines for defining and assessing innovation activities as well as for compilation and use of related data, OECD (2005) introduces 4 types of innovation: product innovation, process innovation, marketing innovation and organizational innovation. Product and process innovations are closely related to the concept of technological developments. A product innovation is the introduction of a good or service that is new or significantly improved regarding its characteristics or intended uses, including significant improvements in technical specifications, components and materials, incorporated software, user friendliness or other functional characteristics (OECD, 2005). Product innovations can utilize new knowledge or technologies, or can be based on new uses or combinations of existing knowledge or technologies.

A process innovation is the implementation of a new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software. Process innovations can be intended to decrease unit costs of production or delivery, to increase quality, or to produce or deliver new or significantly improved products (OECD, 2005). Furthermore, Fagerberg et al. (2005) highlight that while the introduction of new products is commonly assumed to have a clear, positive effect on the growth of income and employment, process innovation, due to its cost-cutting nature, can have a more hazy effect.

The economics literature defines innovation as something new that was created by innovative entities to maximize utility. Endogenous growth theory suggests that innovation activities are positively associated with economic growth (Romer, 1986; Hasan and Tucci, 2010). As a type of innovation, the definition for eco-innovation is as follows: a new or modified process, practice, product, or managerial system that contributes to reduce negative environmental impacts or to reach environmental sustainability targets (Rennings, 2000; Mortensen et al., 2005; Horbach et al., 2013). Eco-innovation shows some specific characteristics compared with general innovation (Rennings and Rammer, 2011). Apart from the benefits brought about by general innovation, eco-innovation brings environmental and economic benefits as the result of positive spillover effects during the internalization of negative environmental impacts. Porter and Van der Linde (1995) refer to this as a win-win situation which allows firms to accomplish their business objectives along with considering environmental protection. Eco-innovation may be developed with or without a particular intention of lowering negative environmental impacts. It can be generated during the process of achieving typical business objectives such as higher profitability or better product quality. Many eco-innovation technologies actually combine corporate benefits with social benefits.

There are several definitions for eco-innovation. One of the widely used definitions illustrates that eco-innovation shows two significant characteristics comparing with general innovation: "It is innovation that reflects the concept's explicit emphasis on a reduction of environmental impact, whether such an effect is intended or not. And, it is not limited to innovation in products, processes, marketing methods and organizational methods, but also includes innovation in social and institutional structures" (Machiba, 2009). Meanwhile, in the EU funded research project, namely "Measuring Eco-Innovation" (MEI) report, Kemp and Pearson (2007) define eco-innovation as "The production, assimilation or exploitation of a product, production process, service or management or business methods that is novel to the organization (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources used (including energy use) compared to relevant alternatives." This definition enhances the previous definition by highlighting two key features: eco-innovation is based on a subjective view of innovation that an innovation as the first introduction of a new product, process, service or organizational structure into the market (Schumpeter and Backhaus, 2003; Fagerberg, 2004). Also the authors include the adoption of innovations previously introduced by others. The inclusion of adoption indicates a focus on the diffusion of technologies. Moreover, the definition of eco-innovation reflects two main consequences of eco-innovation: fewer adverse environmental impacts and more efficient use of resources.

As discussed above, eco-innovation suffers from double externality effect, regulatory push/pull effect (Rennings, 1998; Mortensen et al., 2005; Rennings, 2000). The first characteristic of an eco-innovation is to give rise to a "double externality", that is to say, a positive environmental externality, in addition to the classic knowledge spillovers resulting from any innovation. Externality arises normally as a consequence of market failure. The concept of double externalities comes with reduced environmental investment incentives and external benefits (Beise and Rennings, 2005). Once a new innovation is introduced to the market, imitation from competitors will speed up the diffusion of this new innovation. However, in the private sector, investment in R&D can be repressed when R&D investment outcomes spread out to competitors. Furthermore, specific investment in eco-innovation may be further inhibited due to the fact that the private returns on R&D in green technology is less than its social return if prices are not able to adequately reflect negative externalities (Faber and Frenken, 2009). Thus firms may be reluctant to make further investments to eco-innovation since firms may not be able to fully appropriate the social returns as private returns. Externalities triggered by market failure arise due to unregulated use of rights (Pohl et al., 2015). By improving intellectual property protection, internalization could be reinforced. However, the trade-off is that with regard to environmental incentives for eco-innovation, internalization is likely to slow down the diffusion of environmental friendly technologies in the market. Nevertheless, further internalization requires additional costs since the implementation normally comes with a time lag.

In this thesis, we investigate different aspects of eco-innovation and try to disentangle some interesting questions given the current debate on the characteristics of eco-innovation and the effectiveness of eco-innovation in fighting against climate change. We provide an outline of this thesis below.

In the first chapter, we study the determinants of eco-innovation for French manufacturing firms. Following the theoretical framework adopted by Kesidou and Demirel (2012) and Horbach et al. (2012), we separate the determinants of eco-innovation into those that capture technology push, market pull and regulation pull/push. More specifically, we further examine the framework by investigating the relationship between firms that already invest in the R&D process and the level of engagement in eco-innovation and how this is affected by collaboration within and between firms both locally and abroad. Firms need to handle different technological and economic situations which require different types of resources of knowledge due to the systemic characteristic of innovation. As Horbach et al. (2013) suggested, eco-innovation requires more external sources of skills and knowledge in compared to general innovation. Since the development of eco-innovation requires firms to combine multiple objectives such as production efficiency and environmental requirements and to find appropriate mediation among them, this requires firms to evolve from a closed innovation system to an open innovation mode, leading to a global network of innovation which is referred to the open innovation paradigm (Chesbrough et al., 2006). Furthermore, we examine the effect of environmental management systems (EMS) and regulation stringency on eco-innovation.

Chapter 1 contributes to the existing literature in three ways. First, we investigate whether the sources of R&D activity affects the level of investment of a firm's eco-innovation differentiating between cooperative structures. Different from existing studies which identify four channels of R&D collaboration, including venders, suppliers, competitors and public sectors (De Marchi, 2012; Ghisetti et al., 2015a), we decompose R&D collaboration within and between firms based on the sources of R&D cooperation, namely domestic private, foreign private and public sector cooperation. This decomposition allows for a deeper understanding of the effect of the cross-boarder expansion of R&D transactions and the international innovation networks in stimulating eco-innovation. Second, we consider both command and control (COC) and market-based environmental policy instruments by examining how do strict environmental regulations affect firm incentives to invest in eco-innovation and whether public funding for innovation more generally increases the level of eco-innovation. This approach provides a more comprehensive indication on the modification of the optimal policy mix to promote eco-innovation. Finally, the lack of firm-level data on eco-innovation restricts a generalized conclusion. The existing literature relies heavily on the Community Innovation Survey which only provides limited information on the degree of eco-innovation (De Marchi, 2012; Horbach et al., 2013; Cainelli and Mazzanti, 2013; Ghisetti et al., 2015a). In Chapter 1, we use a unique firm-level panel which allows for an identification strategy that is less sensitive to macroeconomic shocks that may be correlated with country or sector-level eco-innovation and environmental regulations.

Our results show a positive and significant effect of external knowledge sourcing on investment in eco-innovation and that this is primarily driven by doing R&D collaboration with foreign firms. The result holds for both pollution-intensive and non-pollution-intensive firms, however the magnitude of the effect on pollution-intensive firms is a little lower. We also find the importance of implementing EMS in stimulating eco-innovation which continuously improves corporate environmental performance and organizational capabilities. Furthermore, we find that regulation stringency has a significant and positive effect on the level of investment in eco-innovation. Meanwhile, given that eco-innovation is affected by the effect of double externalities, implementation of environmental regulations helps to foster eco-innovation. Although command and control (COC) instruments are significantly effective in promoting eco-innovation, the lack of market-based policy instruments limits the development of eco-innovation in the French context. Taken these results together, we illustrate clear indications for optimizing current policy mix in France to promote eco-innovation.

In the second chapter, we investigate whether more stringent environmental regulations harm firms competitiveness. More specifically, we examine the direct impact of environmental regulations along with the intermediate effect of induced eco-innovation on firms economic performance. The conventional opinion on the economic costs of environmental regulations suggests that stringent environmental regulations impose additional costs which weaken firm's competitiveness in the market (Christainsen and Haveman, 1981; Gollop and Roberts, 1983). In contrast, Porter and Van der Linde (1995) suggest that environmental standards can trigger innovation in firms and therefore allow them to offset the costs of complying with these standards. Firm economic performance may be affected through two channels, first environmental regulations force firms to invest extra capital to meet environmental standards, meanwhile regulation induced innovation may offset the additional costs and even improve business performance.

Chapter 2 contributes to the literature in three ways. First, in addition to productivity (measured by total factor productivity), we also include profitability (measured by operating margin) as a measurement for firm performance. A number of existing studies investigate the effect of environmental regulations on productivity without considering the effect of eco-innovation or only consider general R&D, and the empirical results are mixed

(Jaffe and Palmer, 1997; Alpay et al., 2002; Hamamoto, 2006; Lanoie et al., 2008; Yang et al., 2012; Greenstone et al., 2012; Franco and Marin, 2017). In particular, we focus on regulation induced R&D that specifically targets environmental protection to measure eco-innovation and to illustrate the intermediate effect of eco-innovation. Second, we decompose environment abatement expenditures into two types, product abatement costs and integrated abatement costs. Studies focusing on one specific policy or one specific industry are not able to provide generalized conclusion. Further, instead of evaluating the different types of eco-innovation (Rennings and Rammer, 2011; Nesta et al., 2014; Rexhäuser and Rammer, 2014; Cheng et al., 2014; Van Leeuwen and Mohnen, 2017), our results provide more generalized policy implications on how to formulate a well designed policy mix to decouple the environmental protection from economic growth. Finally, as Cohen and Tubb (2018) point out, most of previous studies use cross-sectional data, country-level or sector-level panel data due to the lack of data availability. Among existing firm-level studies, very few are able to identify the level of eco-innovation which gives our study a further advantage.

In chapter 2, we find that at the current stage, stringent environmental policies reduce total factor productivity (TFP) and meanwhile induced eco-innovations are not able to offset this negative effect for French innovators. Furthermore, we find that integrated abatement expenditures are the main influence on the reduction in productivity. Meanwhile, we find stringent regulations have no impact on firm profitability whereas induced eco-innovation significantly reduces firm profitability in the short term and this significant effect indicates higher initial costs for eco-innovation. Overall, we do not find sufficient evidence supporting the Porter hypothesis that stringent environmental regulations induce efficiency and stimulate innovation which helps firms to become more competitive.

Finally, in the third chapter, we investigate whether eco-innovation can help firms reduce carbon emissions and shift their energy strategies toward a low carbon path. More specifically, we examine the impact of eco-innovation on firms environmental performance measured by CO_2 emissions intensity and fossil fuel intensity. It has been argued that carbon emissions can be reduced by improving energy efficiency and enhancing technological capability (Zhang et al., 2017).

The contribution of this paper is three-fold. First, previous studies investigating the effect of eco-innovation on environmental performance (Lee and Min, 2015; Zhang et al., 2017) only focus on one dimension, CO_2 emissions intensity (Huaman and Jun, 2014; Picazo-Tadeo et al., 2014; Lee and Min, 2015; Zhang et al., 2017; Costantini et al., 2017). Our analysis employs fossil fuel intensity that takes into account the energy mix optimization. With additional measurement, we are able to identify different aspects of environmental performance. Second, our empirical analysis is based on an unique data set at the firm-level which provides detailed information on French manufacturing firms' innovation activities and energy consumption between 2005 and 2012. Such data allows us to investigate the effectiveness of eco-innovation across industries in France. Thus, instead of focusing on just one industry like previous firm-level studies (Zhao et al., 2015; Fernando and Wah, 2017), our sample provides generalized conclusion across all manufacturing sectors in France. To the best our knowledge, this is the first firm-level study investigating the impact of eco-innovation on environmental performance in France. Third, we employ advanced econometric techniques including system generalized method of moments (GMM) and a propensity score matching difference in difference approach (PSM-DiD) to provide a precise examination of the impact of eco-innovation on environmental performance. We take into account the dynamic feature of environmental performance by applying System GMM approach which provides an efficient estimation. Furthermore, to handle the endogeneity concerns regarding the policy effect of eco-innovation on emissions reduction and to control for selection bias, we employ a PSM-DiD method.

Our results in Chapter 3 suggest that eco-innovation does not significantly improve environmental performance for French manufacturing firms over the period 2005-2012. First, we find the decision to invest in eco-innovation does not significantly reduce CO_2 emissions intensity. Meanwhile, investing in general R&D does not significantly reduce CO_2 emissions intensity either. In particular, larger and more mature firms are more likely to have lower CO_2 emissions intensity. Regarding fossil fuel intensity, we do not find any evidence that eco-innovation significantly reduces fossil fuel intensity. However, results suggest that more productive firms in non-pollution-intensive sectors are likely to reduce their fossil fuel intensity. Nevertheless, investing in general R&D would also reduce fossil fuel intensity significantly.

Chapter 1

Is sharing caring? Outsourcing R&D and the impact on eco-innovation expenditure

Abstract

In this chapter we examine how collaboration between firms affects the decision of firms that currently undertake R&D to take the next step and also invest in increasingly complex environmental or eco-innovation. More specifically, we investigate how the decision is affected by the source of R&D funding differentiating between public subsidies and different types of cooperative R&D (domestic private, foreign private and public sector cooperation) as well as regulatory stringency measured by environmental abatement costs. Our unique firm-level sample of French manufacturing firms that already engage in some R&D expenditure means that, unlike studies that use more aggregated data, we are able to use an identification strategy that is less sensitive to macroeconomic shocks that may be correlated with country or sector level eco-innovation and environmental regulations. Our results show the importance of external R&D cooperation (especially with foreign partners) for eco-innovation. We also find that regulatory instruments play an important role in the promotion of eco-innovation. In other results, we show that more productive firms are more likely to undertake eco-innovation. Policy implications are discussed.

Keywords: Eco-Innovation, France, abatement costs

1.1 Introduction

Against a background of growing concerns about climate change and local pollution, firms are coming under pressure to meet increasingly stringent environmental performance objectives alongside their more traditional financial goals. One solution that is thought to increase the ability of firms to meet their environmental obligations, whilst at the same time remaining competitive, is to invest in research and development (R&D) and more specifically, to pursue R&D projects that are targeted at solving environmental problems. If eco-innovation is successful it allows a firm to reduce environmental pressures and at the same time promote sustainable economic growth through the more efficient use of resources (Costa-Campi et al., 2017). However, the process of eco-innovation is becoming increasingly complex, and due to the multiple objectives associated often with eco-innovation, it increasingly requires skills and knowledge from outside a firm's boundaries (Cainelli et al., 2011). Hence, in order to tackle the complexity associated with a reducing a firms' environmental impact, companies are increasingly developing cooperative relationships with a number of actors in their value chain (Ghisetti et al., 2015a; De Marchi, 2012).

The purpose of this chapter is to understand the relationship between firms that already invest in the R&D process as part of their activities and the level of engagement in eco-innovation and how this is affected by collaboration within and between firms both locally and abroad. Definitions of eco-innovation differ in the literature. One definition is to assume that firms eco-innovate when they develop or adopt innovations which diagnose, monitor, reduce or prevent environmental problems (Beise and Rennings, 2005; De Marchi, 2012). Hence, for some firms, eco-innovation simply implies lowering energy costs, managing pollution or reducing greenhouse gas (GHG) emissions more efficiently, whilst for others, it involves designing and applying pollution management and waste control systems and green energy technologies.[1]

Our empirical approach is to construct a panel of French manufacturing firms that undertook some form of R&D between 2004 and 2011 and to investigate the determinants of the level of investment by which a firm chooses to engage in the eco-innovation process. More specifically, our contribution is three-fold. First, we investigate whether the sources of R&D activity affects the level of investment of a firm's eco-innovation differentiating between cooperative structures (the domestic private sector, the foreign private sector and the public sector). Second, we consider both command and control (COC) and market-based environmental policy instruments by examining how environmental regulatory stringency, measured using environmental abatement costs, affects the level that a firm eco-innovates and whether public funding for innovation more generally increases the level of environmental related innovation. Finally, as Del Río et al. (2016) point out, most of the existing literature uses simple cross-sectional data. By using a unique firm-level panel allows for an identification strategy that is less sensitive to macroeconomic shocks that may be correlated

[1]The existing literature defines eco-innovation in a number of different ways. Kemp (2010) defines eco-innovation as the "production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organization (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives". An alternative definition by Rennings et al. (2006) defines eco-innovation as "measures of relevant actors which develop new ideas, behavior, products and processes, and apply or introduce them, and contribute to a reduction of environmental burdens or to ecologically specified sustainability targets".

with country or sector level eco-innovation and environmental regulations. To this end we test five distinct hypotheses that we develop in the theoretical review section of the chapter.

To briefly summarize our results, we find that for French firms, collaboration with foreign partners is an important determinant of a firm's investment in eco-innovation. Furthermore, the results show that different regulatory instruments can play a role in promoting eco-innovation. In other results we find that more productive firms are more eco-innovative.

The remainder of this chapter is organized as follows: Section 2 presents our theoretical framework and a brief review of the existing theoretical and empirical literature on eco-innovation. Section 4 provides a comprehensive description of the data sets and presents our empirical strategy. Section 5 discusses our results. The final section concludes.

1.2 Theoretical background

There is a growing literature that attempts to understand the factors that encourage firms to engage in the eco-innovation process. One common finding is that many drivers of general innovation are likely to be the same as the drivers of eco-innovation (De Marchi, 2012; Hojnik and Ruzzier, 2016). Therefore, policies endorsing general innovation should also result in an increase in eco-innovation. However, eco-innovation also shows some distinctive characteristics. Rennings (2000) emphasizes the role of regulatory push/pull drivers for eco-innovation, derived from a feature unique to eco-innovation called the double externality problem. Eco-innovation encourages the development of environment friendly technologies and these new innovative technologies can result in a technology push effect. However, these new environment friendly technologies may also lead to increased demand and greater competition. This is referred to as the market pull effect. Rennings (2000) notes that eco-innovation in particular needs regulation to coordinate market driven demand and innovation driven environmental technologies.

According to general innovation theory, externalities often arise as a consequence of market failure. The concept of a double externality comes from the conflict between the external benefits from eco-innovation and the arguably weak incentives to invest in eco-innovation (Beise and Rennings, 2005). Although once an innovation is introduced to the market, imitation by competitors will speed up the diffusion of this innovation which is beneficial for the environment, this reduces private investment in R&D outcomes from that investment spill over to competing firms. Moreover, investment in eco-innovation may be inhibited by the fact that private returns on R&D in green technologies are less than its social return if prices do not adequately reflect negative environmental impact (Faber and Frenken, 2009). Thus, firms may be reluctant to devote further investment to environmental R&D, as they are not able to fully appropriate the social returns as private returns. Hence, eco-innovation brings positive externalities, including general knowledge spillovers in the R&D phases as well as the environmental externalities in the adoption and diffusion phases, leading to the social desirability of eco-innovations (Horbach et al., 2013). In addition, if there are significant common knowledge spillovers, so-called environmental spillovers mean that competitors may benefit in terms of reduced regulation costs. As a result, firms devoting resources to eco-innovation face higher costs compared to their polluting rivals, and one of the positive externalities works as a disincentive (Rennings et al., 2006). For this reason, technology push factors and market pull factors push companies towards investment in general innovation, while regulatory push/pull effects should provide a boost to eco-innovation.

In this chapter, we follow Horbach et al. (2012) who distinguish between four categories of factors that have been found to be main determinants of eco-innovation: a technology push effect including inter-firm collaboration, a market pull effect, a regulation pull/push effect and finally, firm specific factors.

1.2.1 Technology push

The technological capability of firms is an important factor in the general innovation literature where capabilities can be either technological knowledge stock or organizational management measures. To build up such capabilities, investment in R&D or human capital and training is necessary. Baumol (2002) describes this as ”innovation breeds innovation”, such that highly innovative firms are more likely to conduct further innovation. However, general R&D expenditure may not always be allocated to eco-innovation. In fact, perhaps surprisingly Horbach et al. (2013) find a negative relationship between R&D expenditure and eco-innovation in their study of French industries such that eco-innovative firms appear to have a lower level of internal R&D compared with generally innovative firms although no such effect was found for German firms.

Focusing on eco-innovation specifically, a number of studies have shown that technological capability is an important driver, especially at the initial development stages (Horbach, 2008). Firms with a higher incentive to innovate and a larger technological stock of knowledge are assumed to have a higher capacity to apply these factors to eco-innovation (Bigliardi et al., 2012). Horbach et al. (2012) consider the need to have R&D that is internal to the firm for it to focus on eco-innovative activities. Focusing on German firms, the authors suggest that internal R&D only affects eco-innovation positively if the target of the innovation is noise pollution reduction. Nevertheless, Cuerva et al. (2014) in a study of small and medium sized enterprises (SMEs) in Spain their cross-sectional study shows a strong correlation between technological capabilities and general innovation but only a small effect for eco-innovation.

Technological cooperation between firms is also considered an important driver of eco-innovation (Cainelli et al., 2011). Solutions to environmental problems are often complex such that a single firm is unlikely to be equipped with all knowledge required to develop and introduce green technologies. In this case, firms may need to access external knowledge from various sources. If eco-innovation requires a cooperative effort, it implies complementarity with activities performed by network partners and may require more cooperation than other types of innovation. Using German data, Horbach et al. (2012) find that collaboration with universities has a positive effect on those innovations that aim to reduce material and energy usage but has no effect on innovation that is targeted at reducing emissions. Horbach (2008), also for German firms, distinguishes between eco-innovation and non-green innovation and suggests that R&D cooperation is more important for green rather than for non-green innovation. It is argued that this result is driven by specific characteristics of green innovation which means that eco-innovation can only be achieved through the combination of a variety of specialist knowledge and competences that are necessarily spread across different types of organization. In order to tackle the complex process of innovation that reduces the environmental impact of firms, companies are increasingly likely to develop cooperative relationships with several actors in their value chain both within and outside of the domestic market. As noted earlier, eco-innovation involves organizational and institutional changes, which add further knowledge requirements for new technology adoption.

In a related study, Ghisetti et al. (2015a) investigate the effect of different external information sourcing on eco-innovation across eleven European countries. By measuring the breadth of external knowledge from a number of different external sources they find a positive effect of a breadth of external knowledge on eco-innovation. However, their results suggest an inverted U shape relationship between the breadth of external knowledge and the intensity of eco-innovation where the marginal return tends to decrease when a firm uses more than six different information sources. Thus, they suggest that it is possible for firms to be “too open”. Nevertheless, Ghisetti et al. (2015a) conclude that the multi-purpose nature of eco-innovation means that eco-innovation usually requires the firm to combine multiple objectives and to find and manage suitable compromises along the way. Typically, an eco-innovator needs to set multiple targets in terms of, for example, production efficiency, product quality, and environmental standards (Horbach et al., 2013). Thus, a broad range of knowledge is needed but can be difficult for the firm to satisfy internally.

Finally, Powell et al. (2005) claim that in advanced fields of research, sources of knowledge are widely distributed, hence cooperation and coordination between all members of the value chain is essential. Hence, firms undertaking eco-innovation may need to acquire external sources of knowledge and skills, and this may be achieved through R&D outsourcing and R&D cooperation (De Marchi, 2012). For example, Cainelli et al. (2011) show that inter-firm network relationships are one of the drivers of eco-innovation for firms located in a local production system, while eco-innovation is triggered by firms' interactions with external sources including universities and suppliers (although it does not appear to be stimulated by interaction with customers and competitors). A more recent study by Schiuma et al. (2013) investigates Italian manufacturing firms and shows that eco-innovation requires a higher recourse to external knowledge, in the form of use of external sources of information and acquiring R&D from external firms. For eco-innovation, cooperation with universities, research institutions and competitors performs a much more important role than for other types of innovation.

H1. Firms that utilize external sources of knowledge devote more resources to eco-innovation

In terms of the relationship between internal R&D intensity and external R&D cooperation, Hemmelskamp (1999) finds that eco-innovators have a lower R&D intensity but that this is compensated for by the use of external sources of knowledge (especially true for product innovations) suggesting that end-of-pipe innovations may require less R&D effort. Mazzanti and Zoboli (2005) suggest that a synergy exists between external R&D cooperation and internal R&D activities and finds that R&D cooperation with external partners complements internal environmental R&D. However, Laursen and Salter (2006) do not find any evidence to support a complementary effect but claim that there is in fact a substitution between the use of external sources of R&D and internal R&D activities.

H2. There is a complementary relationship between external R&D cooperation and internal R&D activities.

In addition to the use of external knowledge, a closely related mechanism is through the enhancement of organizational and strategic capabilities which have also been shown to promote eco-innovation (Kesidou and Demirel, 2012; Pinget et al., 2015). Organizational environmental capabilities are often developed through the use of environmental management systems (EMS). An EMS is a voluntary organizational framework that details the procedures used to manage the impact of the organization on the natural environment (Rennings et al., 2006). Its purpose is to continuously improve corporate environmental performance and is considered to be a strong indicator of the organizational capabilities of the firm with regards to environmental management (Kesidou and Demirel, 2012; Russo and Harrison, 2005).

Several previous studies have stressed the positive impact that EMS has on eco-innovation. For example, Rennings et al. (2006) investigate the influence of different characteristics of the EU environmental management and audit scheme (EMAS) on eco-innovation and find a positive influence of EMAS on the environmental process innovation. The authors also emphasize the importance of the participation of specific departments such as the R&D department as a driver for eco-innovation. Using the Mannheim Innovation Panel (MIP), Horbach (2008) shows a significant and positive relationship between EMS and eco-innovation and suggests that EMS helps to reduce the information deficit that enables firms to detect possible cost savings. The author also claims that general organizational changes and improvements are relevant to eco-innovation. Rennings and Rammer (2009) argue that EMSs represent important internal capabilities for successful environmental technological innovations basing their arguments on the resource-based view of the firm, which emphasize the importance of internal capabilities or resources that are valuable, rare and difficult to imitate or substitute and are therefore fundamental for innovation activities. A more recent study by Kesidou and Demirel (2012) also shows a strong positive relationship between EMS and eco-innovation.

Similarly, Wagner (2007) applies data on environment-related patent applications as well as self-reported environmental innovation to estimate the effect of an EMS on eco-innovation.

Although results suggest a negative effect of EMS on the adoption on firms' general environmental patenting activity, he finds a positive effect on self-reported environmental process innovations. The author notes that under certain circumstances EMS certification may only be a symbolic gesture, in which case the relationship between EMSs and the propensity to implement environmental innovations is rather weak. In addition, firms that implement an EMS are shown to invest more in environmental R&D compared with firms that do not have an EMS. Even though the implementation of EMS signals the building of organizational capabilities, management research on EMS has shown that external certification alone does not boost eco-innovation due to the rather ostentatious organizational implementation of EMS by some firms (Boiral, 2007). Stakeholders often exert influence on managers to adopt accreditation or certifications as a way to prove reputation, therefore performance. Hence, the introduction of EMS can facilitate development and adoption stages of eco-innovation.

H3. Firms that have implemented an environmental management system have a higher propensity to invest in eco-innovation.

1.2.2 Regulation pull/push

Since the majority of environmental problems are characterized by negative externalities, it is argued that eco-innovation is less likely to be driven by traditional market forces. This means that environmental regulations are likely to play an important role in the encouragement of eco-innovation (Horbach, 2008). The majority of earlier studies focus on evaluating the effectiveness of two different regulatory measures, command and control measures (CAC) and market-based instruments (Brunnermeier and Cohen, 2003; Rennings and Zwick, 2002). Only recently has research shifted towards studying whether environmental regulations indirectly stimulate eco-innovation.

The traditional view regarding environmental regulations is that, as regulations increase costs, they will restrict the allocation of resources to technological development and production and hence be damaging to the firms and hence the economy of the country imposing the regulations. The alternative hypothesis, first proposed by Porter and Van der Linde (1995), suggests that stringent environmental regulations could actually stimulate greater innovation. The so-called Porter Hypothesis suggests a so-called "win-win" situation whereby regulations encourage firms to invest in environmental R&D in order to reduce the costs of complying with those environmental regulations. In turn, firms that undertake eco-innovation are subsequently able to reduce their production costs and/or enter into expanding markets for eco-products both domestically and globally.

The Porter Hypothesis has been empirically tested in different contexts and with different data sets. Jaffe and Palmer (1997) estimate the relationship between environmental regulation and innovation in the U.S manufacturing industry. They measure the stringency of environmental regulation using pollution abatement costs as a proxy and examine the relationship with total R&D expenditure, as well as the total number of successful patents. Their results show a positive but weakly significant relationship between regulatory compliance expenditure and R&D expenditure but no relationship between regulatory compliance expenditure and patenting activity, although they were not able to distinguish between environment-related patents and other patent applications.

Brunnermeier and Cohen (2003) extend the previous literature again for the U.S manufacturing industry, to empirically analyse the relationship between environmental regulation and environmental related innovation. Following the previous literature, the authors construct a reduced form model that includes several unique environment related variables. They use the number of pollution related inspections alongside pollution abatement costs as proxies for environmental regulation stringency and examine the determinants of environmentally related patents. Their empirical results show a weakly significant positive relationship between environmental regulations and patents granted. However, the number of pollution related inspections does not significantly affect environmental innovation activities.

Moreover, Popp (2006) shows that after the introduction of air pollution regulation, the number of relevant patents applications significantly increased. Focusing on the U.S, Japan and Germany, Popp (2006) finds a significant increase in the number of patents issued on related abatement technologies following the introduction of more stringent SO2 and NOX standards. Based on these findings, the author claims that stricter environmental standards give rise to greater domestic patenting, but does not have an equivalent effect on foreign patenting implying that firms respond to domestic environmental regulatory pressure, but not to foreign policies. Popp (2006) also tests for international knowledge spillovers by considering the origin of patent citations and argues that earlier NOx related environmental regulations in Germany and Japan played a crucial role in motivating patenting activities in the U.S for pollution control technologies to reduce NOx emissions.

In a more recent study, Demirel and Kesidou (2011) identify three types of eco-innovation, namely end of pipe pollution control technologies, integrated cleaner production Technologies and Environmental R&D and test the effect of environmental regulations on different types respectively using firm level UK data. Their results emphasize the important role of policy intervention in stimulating eco-innovation. And finally, Lanoie et al. (2011) show that environmental regulation encourages firms to re-allocate R&D expenditures towards environmental innovation. According to Lanoie et al. (2011), the weak Porter Hypothesis, which suggests that environmental regulation stimulates innovation in terms of green R&D investment, holds and that investment in environmental R&D also has a positive effect on firm performance.

H4. The stringency of environmental regulations stimulates eco-innovation.

The empirical evidence with respect to the use of other policy measures, namely subsidies for environmental R&D, has been investigated by itself and in combination with other market-based instruments and regulation. Johnstone et al. (2008) report on three different case studies: abatement technologies for waste water effluent from pulp production; abatement of motor vehicle emissions; and the development of renewable energy technologies. Overall, the case study evidence supports the argument that environmental policy can increase the propensity of a firm to engage in technological innovation. In line with previous findings, Johnstone et al. (2010) also show that environmental policies significantly affect private innovators, although the strength of the effect varies over different technologies.

As argued above, the use of combined regulatory instruments can help economies not only reduce the negative environmental impact but also provide incentives to the private sector to devote resources to eco-innovation. The presence of public support in the case of subsidies is particularly crucial for developing green technologies due to the specific characteristics of eco-innovation. Theoretically, Acemoglu et al. (2012) show that although a carbon price alone could simultaneously control both environmental and knowledge externalities, such a course of action would lead to lower economic growth due to higher costs. In addition, they showed that keeping other policy instruments inactive, the sole use of subsidies would lead to excessively high levels of subsidies and could potentially lead to a substitution of subsidies for proactive environmental R&D investment.

Empirically, Veugelers (2012) shows very little support for the efficacy of subsidies targeted at innovation to reduce CO2, when used in isolation. However, Veugelers (2012) suggests that a combination of regulations and taxes with subsidies, particularly for the adoption of innovation to reduce CO2 emissions can have an overall positive effect. Costa-Campi et al. (2017) also provide an insight into which public policies are more effective in triggering investment in by examining the relationship between environmental innovation R&D expenditure and a range of policy instruments, including environmental regulation and other policy measures including R&D subsidies and environmental taxes. Their results for 22 manufacturing sectors in Spain for the period 2008–2013 that a policy mix of environmental, energy and technological regulatory measures is the most effective combination of policies. However, they also point out that innovation is not a short term process and that it can take a long time to develop a technology in response to existing environmental regulation with a short term negative impact on profits.

H5. Firms that receive public subsidies are more likely to invest in eco-innovation.

To summarize, we argue that existing firm-level studies have not yet reached a consensus whether the stringency of environmental regulations stimulates eco-innovation. The majority of empirical evidence on the relationship between environmental regulation and eco-innovation comes from a relatively small number of countries including the U.S, Germany, Italy and the UK and a strong reliance on German data and often for a single year of data.

1.2.3 Firm specific factors

Finally, we consider the role of other firm specific factors and firm heterogeneity. For example, firms that engage in eco-innovation may already be the pro-active firms and hence may not react to more stringent environmental regulations since they may already be in compliance with the new regulations by already having lower emissions intensity. In contrast, stricter environmental regulations may promote eco-innovation for the previously less innovative firms, which only adopt eco-innovation as a measure of reducing higher production costs that arise due to the need to comply with the stricter environmental regulations.

When we consider other firm-level characteristics, many previous studies find a positive effect of firm size on general innovation where the positive effect holds when other factors such as firm age are controlled for. For studies that concentrate on eco-innovation, a positive effect of firm size on eco-innovation is also expected. The existing literature provides a number of explanations. Horbach (2008) reports that firm size positively affects innovation but not eco-innovation where the positive effect for innovation is put down to large firms having greater access to financial and human resources (Rave et al., 2011). Kesidou and Demirel (2012) use four thresholds for size, namely micro, small, medium and large and find that large firms with over 250 employees spend six times more on average on environmental R&D compared to medium sized firms with more than 50 but less than 250 employees. The authors claim that larger firms' higher propensity to eco-innovate could be due to a higher public visibility and hence greater pressure from the public to appear be environmentally friendly. A latter study by Horbach et al. (2013) shows a significant and positive link between firm size and eco-innovation intensity in France and Germany arguing that it is because eco-innovation realized by larger firms. Similarly, Przychodzen and Przychodzen (2015) investigate the effect of firm size on eco-innovation in Poland and Hungary and also find that eco-innovation is normally undertaken by significantly larger firms. Taking a segmentation approach, Del Río et al. (2017) find that the lack of eco-innovative incentive of SMEs is due to the restriction of internal technological capabilities, although in their study they were unable to distinguish between R&D related employees and other employees.

Firm age also differs between firms. The theoretical literature on general innovation suggests that older firms have had longer to accumulate internal capabilities, which should have a positive effect on innovation in general (Sørensen and Stuart, 2000). Similarly, one should expect this argument to hold for eco-innovation under the assumption that younger firms tend to put survival first and prioritise seeking market opportunities (Mazzarol et al., 2010). Wagner (2007) reports a significant positive association between firm age and the likelihood of carrying out process eco-innovation although the effect of firm age is insignificant for product eco-innovation. However, the majority of authors show an insignificant influence of age on the propensity to engage in eco-innovation (Ziegler, 2015; Horbach, 2008; Rave et al., 2011; Del Río et al., 2017).

Given that eco-innovation can be considered as a costly investment with risky returns (more so that general innovation), financial constraints or difficulties in obtaining credit may reduce the possibility that a firm devotes resources to eco-innovation. Access to adequate financial resources is considered essential to drive economic growth, however, due to the specific characteristics of eco-innovation, financial resources are also particularly if a firm is to start the process of eco-innovation (Ghisetti et al., 2015b).

The degree of eco-innovation can be expected to also differ across sectors. The innovation intensity of a particular sector depends on factors such as the maturity of the dominant technology, scale, capital intensity, R&D intensity of the industry and general competitiveness. Sectoral differences and their influence on eco-innovation are usually addressed through the inclusion of the sectoral dummy variables or otherwise through broader definitions of what constitutes a dirty or pollution intensive sector with the general finding that highly polluting sector sectors are more likely to eco-innovate (De Marchi, 2012).

1.2.4 Market pull

While regulation still seems to be necessary to overcome the double externality problem, existing studies indicate that there is no strong stimulus for eco-innovation from the demand side since eco-friendly products are still too expensive (Rehfeld et al., 2007). Although it is argued that consumers can also drive innovations (Horbach, 2008; Van den Bergh, 2008), this argument is only partially supported by empirical evidence. In particular using German manufacturing firms, Horbach (2008) illustrate demand as the increase in expected turnover and empirically shows that demand factors are an important determinant of eco-innovation. Furthermore, following previous studies, Wagner (2007) classifies stakeholders into three different groups based on the intensity of their environmental concern. The author underlines that firms with predominantly environmentally concerned stakeholders are more positively associated with eco-innovation. The above literature also examines the impact of demand factors upon a binary dependent variable which suggests that the decision of firm to eco-innovation. Meanwhile, Kesidou and Demirel (2012) push the discussion further by using R&D intensity as the dependent variable to study the market pull effect taking corporate social responsibility (CSR) and customer requirements into account. In a study of UK manufacturing firms, they find little evidence to support the argument that demand factors boost investment in eco-innovation.

1.3 Data and empirical strategy

1.3.1 Data

In this study we use firm-level data for France. Our motivation for concentrating on French firms is two-fold. First, as the third largest economy in the EU, France assigns significant resources to R&D activities which were approximately 4,8643 millions Euros in 2015 which ranked second in the EU. These R&D expenditures account for approximately 2.23% of total French GDP which is ranked seventh in the EU (Bank, 2017). In the ranking of innovation outputs, France came eighth worldwide for the number of patents issued, with a total figure of 13,315 patents granted in 2010 (Commission, 2016). Second, France has a strong track record in environment protection. In the latest Environmental Protection Index, France ranks 10th among 180 countries worldwide (YCELP and Yale, 2016) and consists of a combination of governmental policies and regulations, technological innovations and significant growth in the provision of eco-industrial parks (EIP).[2] In terms of eco-innovation, France's eco-industry sector ranks fourth in the world by size and is the second largest in the EU (Commission, 2016). In 2011 the total production from eco-industry reached 79.3 billion and growth in the production of these industries was stronger (+7.5%) than total economic activity (+4.2%). In terms of employment, around 455,600 people worked full-time in the green economy, while exports related to eco-activity was approximately 1.9 billion Euros.

In this study, we construct an unbalanced panel data set to investigate what determines the decision of an existing innovator to engage in eco-innovation. To do this we merge four different data sets. First, we use the Annual Survey on the Resources Devoted to R&D Activities (Enquete annuelle sur les moyens consacres a la R&D) collected by the French Ministry of Education and Research that consists of over 7,000 firms that perform R&D activities and invest more than 350,000 in innovation and a sample of the remaining companies that dedicate fewer resources to R&D. The resulting data set provides a good representation of the innovation activities carried out by French firms in terms of internal and external resources, the number of employees working for the R&D department, public funds received, the number of patents and indicators of product and process innovations.[3]

[2] The term eco-industry refers to all economic activities that provide technical solutions for (downstream) environmental protection. This includes activities from filtration systems for air pollution to waste management and has recently been expanded to include clearly defined and tangible renewable energy (Jänicke, 2012).

[3] Note that all firms in this data set are innovators. Due to the sampling structure, firms that only

The next stage is to merge in financial information on manufacturing firms that comes from two main data sets. The first is the Unified and Comprehensive File of SUSE (FICUS) database that is based on an annual fiscal census of firms called the Unified Corporate Statistics System (SUSE) which is conducted by the French Ministry for the Economy and Finance. SUSE covers all firms that are under the industrial and commercial benefit (BIC) tax system or under the non-commercial benefit (BNC) tax system that means SUSE comprises all firms that send a tax return to the French Ministry for the Economy and Finance. The result is an unbalanced panel that comprises over 3 million manufacturing firms for a period of 14 years between 1994 and 2007. Three kinds of variables are available. First, there is firm information such as the primary industry classification at the 4-digit NACE level, employment and date of creation. Second, there are income statement variables such as total turnover, total labour cost and total gross earnings. Third, there are balance sheet variables such as debt and capital stock. The second data set with complementary financial data is the Approached File of ESANE Results (FARE) which is the new Annual Business Statistics Production data that replaced FICUS from 2008. Hence, to obtain fiscal data from 2008 we use the FARE file that gives an unbalanced panel covering the years 2008 to 2012.

Finally, the fourth data set comes from the ANTIPOL survey that we use to construct our

invest relatively small amounts in R&D are randomly selected. Thus, a problem with this data set is missing values and firms with long year gaps between observations. To obtain a consistent panel we drop firms with more than six year gaps between data points from our sample. After removing those firms use extrapolation techniques to fill in missing observations.

firm-level environmental variables. The survey asked 10,000 plants about their investment in capital to control pollution. Until 2005, the survey was a census of plants having at least 100 employees whatever their activities. This threshold was reduced to 50 or 20 employees for pollution intensive activities. After 2006, ANTIPOL become a census for plants that have at least 250 employees and a survey for other plants stratified by activities and by size group. ANTIPOL asked plants how much they invest in end-of-pipe technologies and integrated technologies to prevent the emissions of seven pollutant categories: (1) waste water; (2) non-radioactive waste; (3) climate pollutant; (4) noise and vibration; (5) land and water pollutant; (6) biodiversity and (7) landscape and other pollutants. The advantage of the survey is that it explicitly excludes workplace health, securities and hygiene questions and focus exclusively on pollution control. To obtain a firm level data set we aggregate the plant-level data to the firm level by subtracting the first 9 digit SIREN code which is the unique French business identification number from the 16 digit SIRET code. Firms that have no plant showing in ANTIPOL are excluded from the sample. We assume that any missing pollution abatement expenditure from ANTIPOL are very small in comparison to reporting plants. A robustness check tests our aggregation assumption.[4]

After merging the four data sets we remove inconsistent observations and coding errors from our sample (for example, incomplete data, negative values for R&D expenditure and other

[4]This assumption may have an impact on our main results that if a firm has several plants below the threshold that are not surveyed by ANTIPOL and a large plant that is surveyed by ANTIPOL, under the previous assumption, then this firm's total pollution abatement expenditure equals to the firm's large plant expenditure. However, if the summation of the small plants' expenditures is not small comparing to the large plant, then the firm's total expenditure is underestimated. This measurement error could lead to biased coefficient of interest.

contradictory information). In addition, we drop firms with less than 10 full-time equivalent employees. All monetary variables are in thousands of Euros and have been deflated using a French Producer Price Index at the sector level with 2010 as a baseline (INSEE, 2017). Our final sample is an unbalanced panel of almost 7,300 observations for around 2,200 French manufacturing firms over an 8 year period. We also distinguish between pollution intensive sectors and non pollution intensive sectors following Shimamoto (2017) who categorises the five most pollution intensive sectors as (1) Manufacture of pulp, paper and paper products, (2) Manufacture of chemicals, chemical products and man-made fibres, (3) Manufacture of coke, refined petroleum products and nuclear fuel, (4) Manufacture of other non-metallic mineral products and (5) Manufacture of basic metals and fabricated metal products.

1.3.2 Empirical strategy

1.3.2.1 Dependent variables

There are various different measures of eco-innovation. Arundel and Kemp (2009) describes four although the most widely used are first, environmental research and development (R&D) expenditure and second, the number of green patents.[5] Environment related patents and investments in environment protection have been widely adopted as proxies for eco-innovation (Jaffe et al., 1995; Jaffe and Palmer, 1997), and these two types of measure

[5]Other measures of eco-innovation described in Arundel and Kemp (2009) include direct output measures such as data on the sales of new products and indirect impact measures that are derived from aggregate data such as changes in resource efficiency and productivity.

are considered to be environmental R&D input or environmental R&D output measures.[6]

In this chapter we use environmental R&D expenditure at the firm level as our proxy for eco-innovation. Measures of industry and firm level environmental R&D have been used in a number of previous studies although they tend to have as their dependent variable subjective measures of the motivation to undertake eco-innovation that are obtained from different survey data sets (Del Río et al., 2011; De Marchi, 2012; Del Río et al., 2017; Jové Llopis et al., 2017). Unlike previous studies, firms in our sample are specifically asked how internal R&D is allocated and one of the categories is the percentage of R&D expenditure dedicated to the protection of the environment. Our environmental R&D expenditure variable is therefore constructed by multiplying the share of environmental R&D expenditure by total internal R&D expenditure. This variable captures the extent of a firm's internal R&D investment in eco-innovation, and is more precise than previous R&D based eco-innovation indicators employed in the literature. Surveys investigating environmental R&D activities often ask firms whether they conduct environmental R&D but do not specifically ask about environmental R&D intensity (Horbach, 2008). In a number of early studies, total R&D expenditure was used as an indicator of eco-innovation (Jaffe and Palmer, 1997; Brunnermeier and Cohen, 2003) based on the assumption that there is a strong correlation between eco-innovation and general innovation although this is potentially problematic as eco-innovation could crowd out general innovation. Thus, an advantage of our approach is

[6]Although useful, patent counts have a number of limitations as a record of eco-innovation (Veugelers, 2012) as it is often difficult to value different patents. For example, the patent count gives the same weight to patents with no commercial values and those which are highly profitable. Hall et al. (2007) highlight that the distribution of the value of patents is highly skewed, thus only a fairly small number of patents actually have any commercial value and could impact any analytical results.

that we have a direct measure of the investment in eco-innovation: log transformed variable "Log_EnvR&D" is based on the exact environmental R&D expenditure of a firm.

1.3.2.2 Explanatory variables

With respect to our explanatory variables, our key variables are based on information on R&D cooperation with external partners. First, we include a dummy variable "ExtR&D_d" that indicates if the firm was subcontracting and collaborating on R&D with external firms or institutions. Furthermore, we include the log transformed variable "Log_ExtR&D" which illustrates the level of R&D expenditure that has been subcontracted and collaborated with external firms or institutions. Nevertheless, the R&D data identifies three types of external partner: (1) the foreign private sector, (2) the private sector in France and (3) the public sector (including higher education and public organizations) and more specifically, partners from the public sector that includes both domestic and international partners. Thus we test both Binary variables and continues variables indicating if the company cooperates with any of those partners have been created to distinguish between the different roles of different partners toward eco-innovation. Following De Marchi (2012), the variable "R&D_intensity" expresses R&D intensity as the ratio between the number of R&D activities related employees and the total number of employees. Moreover, we include the interaction term between "ExtR&D_d" and "R&D_intensity" and the interaction term between "Log_ExtR&D" and "R&D_intensity" to test for the complementarity hypothesis (H2). We also include public funding as an control for firm's innovation structure. Our public funding variable includes all funding received by firms for R&D activities from public resources and the variable "Pubfunding_d" is equal to one if the firm received any public funding.

To capture information about the organizational capability of a firm we measure a firm's engagement with environmental management systems. In line with Kesidou and Demirel (2012) and Costa-Campi et al. (2017) we also consider ISO 14001 approval to be one of the most widely used measures of a firm's commitment to having an operational environmental management system alongside having an Eco Management and Audit Scheme (EMAS). ISO 14001 can be used by any firm, regardless of its activity, and is granted once a firm sets up an environmental management system and obtain a certificate for their productive process. ISO 14001 has been frequently included as a determinant of eco-innovation and has been found to be effective in stimulating environmental R&D. Information of ISO 14001 accreditation is obtained from the ANTIPOL data set and has been available since 2002. Furthermore, with regard to organizational capability, the ANTIPOL data set provides two more variables "sme" and "EMS_process". "SME" is a binary variable which equals one if a firm has some other sort of environmental management systems other than ISO 14001. "EMS_process" is a binary variable which equals one if a firm is in the process of obtaining environmental certificate. Since all these variables are at plant level and it is possible that only one plant among several plants for a firm has environmental managements systems we assume that if a plant of a firm is accredited environmental management systems, then this firm is also accredited with having an environmental management system. After aggregating to firm level, due to the fact that "ISO" and "SME" variables only partially capture the effect of a firm's environmental management system, we construct a new variable namely "EMS" which equal to one if a firm is accredited ISO 14001 or any other environmental management systems.

To capture the effect of environmental regulations, we introduce a policy variable that the previous empirical literature had tended to include as a determinant of eco-innovation, namely environmental abatement costs. Environmental regulation are thought of an effective tool for encouraging firms to devote resources to eco-innovation. Institutional pressure from stakeholders is also thought to trigger eco-innovation and more so among high polluting firms (Berrone et al., 2013). We proxy the stringency of environmental regulations using environmental abatement cost expenditure. This is done by summing the total integrated and end of pipe investment across different pollutant categories from the ANTIPOL data set that gives us a measure of total abatement costs. More specifically, this variable includes expenditure that is the result of the operation of abatement capital, expenditure due to environmental taxes and expenditure due to environmental management such as the training of managers or the purchase of services. Since abatement intensity becomes relatively small when we scale abatement expenditure by total output, we transform this variable into percentage by multiplying it by 100.[7]

In addition to our key variables of interest we also include a series of controls. To control for the possible effect of exporting on degree of eco-innovation we include a binary vari-

[7]These expenditures exclude expenditure for labour health and security and expenditure that allows a reduction of material or energy use.

able "Export_d" using information on the exports of manufacturing firms from the Unified and Comprehensive File of SUSE (FICUS) database and the Approached File of ESANE Results (FARE). To the extent that access to foreign markets may lead to exposure to new products and ideas we would expect more innovation from exporters. In particular, if consumers in foreign markets demand green products it provides an opportunity for the firm to charge premium prices and increase returns to eco-innovation. Similarly, foreign ownership provides firms with greater exposure to international markets and provides network opportunities with foreign firms that may improve environmental efficiency and opportunities for eco-innovation through environmental technological spillovers and through possible exposure to institutional pressures from foreign governments and other overseas stakeholders(Cainelli et al., 2012). Multinational corporations (MNCs) may also obtain financial benefits from the adoption of a standardised environmental strategy which may allow them to offset the initial cost of complying with environmental regulations (Costantini and Mazzanti, 2012). Hence, we include two firm ownership dummy variables, namely "French_group" and "Foreign_group" where a firm is considered to be part of a larger French group if 50% of the equity is owned by a larger domestic company and similarly if 50% of the equity is owned by a foreign group. To control for the effect of financial constraints on eco-innovation, we also include a measure of leverage by including a firm's debt-to-equity ratio measured as Debt divided by (Debt plus Equity) (Lee and Min, 2015).

To control for a firm's productivity we calculate total factor productivity (TFP) following Doraszelski and Jaumandreu (2013). Building on Levinsohn and Petrin (2003), Doraszelski and Jaumandreu (2013) show that we can endogenously consider the link between R&D and productivity without explicitly modeling how the knowledge capital accumulates. Hence, we include lagged R&D expenditure as an additional instrument in the production function. Nevertheless, since the assumption that total wages equals to labour productivity can fail (Syverson, 2011), we proxy labour using the log of the number of full-time equivalent employees.

Finally, we include a series of standard control variables. Firm size is included and could be positive or negative since size provides a scale advantage but could be negative as small firms are perceived to be more flexible especially in terms of adopting new technologies. Firm size, "Log_size" is measured as the log of the number of full-time equivalent employees. We also include firm age as an indicator for accumulated organizational resources and is expected to positively relate to technological innovation, although as with size, younger firms may be more innovative as a way to increase market share. Our variable "Log_age" is measured as the log of age in years generated by deducting firms' creation year from the current year. Likewise, because efficient firms are more likely to survive and grow (Pinget et al., 2015), firm age is likely to have a positive impact on eco-innovation. We control for the input prices by including a control variable "Log_avewage" which is a proxy for the price of labour measured as the ratio between salaries paid to the employees and firm total number of employees. To take into account invariant characteristics we use year dummies and two-digit NACE sector dummies to control for business cycle effects common to all businesses. We also include regional dummies for the 25 administrative regions.[8]

[8]The 25 administrative regions include 22 regions in Metropolitan France and 3 overseas regions. Since

1.3.2.3 Model specification

In this chapter we apply a range of econometric techniques to understand how external co-operation between firms and institutions can influence eco-innovation controlling for firm heterogeneity. First, in order to benchmark our findings we test for the determinants of eco-innovation but with the addition of extra control variables. Since changes in firm characteristics, such as firm size may induce firms to switch to invest in green R&D, they may also affect other firm characteristics such as R&D intensity. Hence we lag all independent variables by one year to mitigate possible endogeneity concerns. Hence, we estimate the following baseline model that allows us to test our various hypotheses:

$$Log\_EnvR\&D_{i,t} = \beta_1(F_{i,t-1}) + \beta_2(T_{i,t-1}) + \beta_3(P_{i,t-1}) + \mu_i + \gamma_t + \epsilon_{i,t} \tag{1.1}$$

where F, T and P are vectors of explanatory variables, while Log_EnvR&D indicates the log transformed level of resources that the firm dedicates to eco-innovation in year t.

Table 1.1 defines our variables. In the first set of variables F, we include those control variables that have been identified in the literature as firm specific factors (Del Río et al., 2017) and includes firm age, firm size, average wage, ownership of firm, TFP and leverage. Then in the second set of variables T, we include a series of variables to capture tech-

in 2014, the French parliament passed a law reducing the number of metropolitan regions from 22 to 13 effective 1 January 2016, we adopt the previous legal concept of a region.

nological capabilities and includes R&D intensity, our external cooperation R&D dummy, public funding dummy, "EMS" dummy and "EMS_process" dummy. Finally, we include abatement intensity as our policy instrument in set of variables P. In addition, we take into account time-invariant characteristics through random effect μ and fix parameters of time, sector and regional dummies, namely γ_t. Sector dummies are included to control for time invariant factors common to firms across different sectors respectively and include year dummies to account for business cycle effects.

[Table 1.1 about here]

Due to the sampling structure of the R&D data that includes only large innovators that invest more than 350,000 in innovation and a sample of the remaining companies that dedicate fewer resources to R&D, we observe a large number of zero observations for our dependent variable. Hence, we estimate a Tobit model. This implies that our dependent variable "Log_EnvR&D" is an observed realisation of an underlying latent variable that describes the intention of a firm to engage in environmental R_D activities. Thus, when this intention is positive, we equate the observed variable to the latent variable $Log\_EnvR\&D_{i,t} = Log\_EnvR\&D^{*}_{i,t}$. When the latent variable is zero, our measurement variable equals zero, thus $ln\_envrd_{i,t} = 0$. So:

$$Log\_EnvR\&D_{i,t} = \begin{cases} Log\_EnvR\&D^{*}_{i,t} & \text{if } Log\_EnvR\&D^{*}_{i,t} > 0 \\ 0 & \text{if } Log\_EnvR\&D_{i,t} = 0 \end{cases}$$

We calculate marginal effects to allow comparisons across models. However, a number of endogeneity concerns remain unresolved. First, there could still be other factors in the error term that are correlated with a firm's eco-innovation investment. Second, there could be reverse causality if environmental R&D causes a change in productivity. Third, policy-makers may introduce less stringent regulations in a particular sector if they observe that the productivity of this sector is low or is falling. Our solution to address such endogeneity problems is to impose a lag structure to control for the delayed effect of the independent variables on eco-innovation and to resolve the reverse causality concerns.

1.3.2.4 Descriptives

We begin with a description of our data. The sample we use in our econometric analysis consists of 2,197 French manufacturing firms and 7,238 observations between 2004 and 2011. Of the 2,197 firms, 754 firms have done some environmental R&D investment, which represent 34.09% of the firms in our sample. Table 1.2 presents the summary statistics for our independent variables. The average size of the firm is approximately 600 full-time equivalent employees thus our sample consists of relatively large firms. Likewise, the average export is around 95% which shows that a large majority of firms in our sample are exporters, again a result of our sample being restricted to relatively large firms.

[Table 1.2 about here]

In terms of our main variables of interest, over 60% of firms do some degree of external R&D with around 20% of firms having at least some external R&D overseas and around 28% including public institutions in their R&D process. Nearly half of all firms domestically outsource at least some of their R&D process domestically. In terms of our policy variables around 25% receive some degree of public funding and over 70% have some sort of environmental management systems in place.

In Table 1.3, we present the annual average R&D expenditure and annual environmental R&D expenditure. Although R&D expenditure remains relatively stable over time (with a dip following the financial crisis in 2009), the average value of eco-innovation has continued to increase over this time period. Figure 1.1 plots environmental R&D expenditure intensity over time and shows that average eco-innovation intensity increased from just over 3% in 2004 to nearly 7% in 2011. Figure 1.2 plots the percentage of firms with an environmental management system distinguishing between eco-innovators and general innovators showing that eco-innovative firms have a higher rate EMS implementation. Thus, it appears that eco-innovators devote greater resources to environmental protection.

[Table 1.3 about here]

[Figure 1.1 about here]

[Figure 1.2 about here]

In terms of our abatement intensity variable, Figure 1.3 indicates that average abatement cost intensity did not vary much between 2004 to 2011. This may be explained by the fact that French manufacturing industry is highly developed and that France had introduced consistent and relatively strict environmental policy prior to our period of analysis. Given that there were no significant environmental policies introduced during this period a relatively stable percentage might be expected although another explanation is that stricter environmental policies were prevented by business lobby groups whilst at the same time, the implementation of new policies was often slowed as a result of bureaucratic administrative structures (Adelman and Engel, 2007).

[Figure 1.3 about here]

Table 1.4 presents the distribution of environmental R&D investment for firms across different sectors where we observe considerable sectoral variation in the adoption of eco-innovation although the average intensity remains below 10% of total R&D expenditure with the exception of (sector 40). However, Figure 1.4 shows that there is no substantial difference in environment R&D intensity between pollution intensive sectors and non pollution intensive sectors. For example, the environmental R&D intensity for manufacturing of machinery is close to manufacturing of basic metals.

[Table 1.4 about here]

[Figure 1.4 about here]

In Table 1.5 we group firms into polluter and non-polluters following. In our sample, 580 French manufacturing firms are classified as pollution-intensive representing 26.22% of the firms in the sample. From Table 1.5 we observe that polluters appear to be on average more productive, pay lower wages and are smaller in size. Nevertheless, polluters have a higher R&D intensity as well as a higher level of investment in environmental R&D and are more willing to cooperate with external partners. Not surprisingly, polluters have a higher abatement intensity but also have a higher rate of implementing an environmental management system. Figure 1.6 shows that a higher share of polluters have an environmental management system in place compared to non-polluters with both groups exhibiting a slight upward trend in EMS attainment.

[Table 1.5 about here]

[Figure 1.6 about here]

Figure 1.7 provides evidence of the distribution of R&D across France and maps the location of innovators in our sample across regions. Larger clusters are represented by the darker shaded areas. In particular, innovators seem to be particularly clustered in the Ile-de-France, the region surrounding Paris, where most of the multinational enterprises

(MNEs) and of research institutions are located, or in Rhone-Alpes, the region bordering Germany.

[Figure 1.7 about here]

1.4 Empirical results

We present our main results in Table 1.6 and Table 1.7. The parameters reflect the impact of a change in the control variables on the level of resources that are invested in eco-innovation activities. In Table 1.8 we separate our sample into pollution intensive sectors and non pollution intensive sectors. We employ the random effect Tobit model and to help with the interpretation of the coefficients, we report the marginal effects. We first look at our baseline model in Table 1.6 which investigates the firm's level of investment in eco-innovation activities.

First, in Table 1.6, as a test of **H1**, Model (1) shows a positive and significant effect of external R&D cooperation on a firm's level of investment in eco-innovation. Compared to firms that had not previously outsourced R&D to external partners, firms that engaged in R&D cooperation in the previous period invest 6.7 percentage points more in eco-innovation activities in the current period. When we regress eco-innovation on the different types of cooperation agreement with our three different categories of partners in Specification (2), we find that it is firms that cooperate with foreign firms that has the main influence on the level of investment in eco-innovation by the firm in France. Thus, we confirm **H1** that overall R&D cooperation with external partners promotes eco-innovation but that for French firms it is cooperation with foreign partners is driving this result rather than domestic partners or cooperation with the public sector and universities.

Second, from model (2) in Table 1.6, we find a negative but insignificant effect of R&D intensity on eco-innovation. One possible explanation is that eco-innovation is too expensive in the initial stages prior to diffusion, since private returns on environmental R&D are less than it's social return if prices do not adequately reflect negative environmental impact. The insignificant effect may be caused by substitution between the use of external sources of R&D and internal R&D activities as discussed by (Laursen and Salter, 2006). To test the complementary/substitution argument that underpins **H2**, we report models with different specifications of the variable measuring internal R&D effort in model (3) (excluding internal R&D) and (4) which includes an interaction term between R&D_intensity and our external R&D dummy. In each case our external R&D cooperation variable remains positive and significant. However, as the interaction term is insignificant we are not able to accept **H2** that there is complementary between external R&D cooperation and internal R&D intensity. Such finding is interesting in terms of policy implications since it gives support to the idea that eco-innovation must be supported by policy which helps to improve knowledge spillover as well as public–private partnerships in order to help firms to overcome innovation barriers.

To test **H3** on the role of organizational capabilities, the results show across all models (1)-(4) that the implementation of an environmental management system (EMS) promotes eco-innovation and is a finding that is consistent with previous studies (Kesidou and Demirel, 2012). Our findings indicate that, compared to firms that had no EMS, firms that had an EMS in place in the previous year devote on average 6.6 percentage points more in eco-innovation. The results confirm **H3** that firms which build organizational capabilities accumulate necessary technologies that enable them to invest in eco-innovation.

We now consider the role of regulatory and policy instruments in encouraging a firm to invest in eco-innovation. In line with the literature (Kesidou and Demirel, 2012; De Marchi, 2012; Horbach et al., 2013; Costa-Campi et al., 2017), we find that policy instruments are important drivers of eco-innovation. Looking first at the abatement intensity, we find a positive and significant effect of abatement expenditure intensity on a firms investment in eco-innovation. The interpretation of the coefficient in Model (1) is that a 1% increase in the mean abatement intensity is expected to increase the expenditure in eco-innovation by 6 percent points on average. Since we use abatement intensity as a proxy for policy stringency, we confirm **H4** that firms are motivated by stringent environmental policies to undertake eco-innovation.

In contrast, the results for our public funding variable is positive but insignificant. Unlike Horbach (2016) who finds a positive and significant coefficient for environmental subsidies, our insignificant effect is closer to Cuerva et al. (2014) who conclude that public funding is not relevant as a way to explain eco-innovation among low tech firms. Thus, our results suggest that, although general public funding such as subsidies promote general R&D activities, they do not appear to affect the level of investment in eco-innovation. In this case, **H5** is rejected.

In terms of our other control variables, results from different specifications show that lagged TFP has a positive and significant impact on the investment in environmental R&D of firms across all specifications. Our results suggest that more productive firms are likely to invest more in eco-innovation. The other consistently positive and significant determinant of eco-innovation is firm size and suggests that larger firms on average devote more resources to eco-innovation. Kesidou and Demirel (2012) claim that Large firms are more likely to invest in environmental R&D because of their relatively higher public visibility and the corresponding social pressures from both society and government. Thus, beside the traditional advantage for large firms to be able to devote significant resources to general innovation this argument also appears to apply to eco-innovation as well as firms being more able to satisfy society and government requirements (De Marchi, 2012; Cuerva et al., 2014; Del Río et al., 2017). However, as shown previously in Table 1.2, the average size of the firm in our sample is approximately 600 full-time equivalent employees which suggest our sample consists of relatively large firms. Regarding our export status dummy, we find positive but insignificant effect on eco-innovation. This is potentially due to the high participation rate of export in our sample. From Table 1.2, we observe over 95% of observations export. This large proportion thus do not display significant impact on the decision to devote to eco-innovation.

[Table 1.6 about here]

In the next stage we replace our external R&D dummies with with their continuous equivalents. Hence, in Table 1.7, instead of dummy variables for external R&D cooperation, we estimate the model using the level of external cooperation R&D which is measured by natural logarithm of external R&D investments in Model (1). In Model (2), again we decompose the level of external cooperation R&D into three different sources of external cooperation R&D. Model (1) shows a consistent positive and significant effect of level of external R&D cooperation (level of R&D outsourced)on a firm's level of investment in eco-innovation. The coefficient indicates that firm devoted 1% more in R&D cooperation (level of R&D outsourced) would increase their current eco-innovation expenditure by 0.01%. When we distinguish between the three sources of external cooperation R&D in specification (2), we also find that the level of R&D outsourced to foreign firms is positively correlated with the level of investment in eco-innovation. Overall, we find consistent results when we replace our external R&D dummies with with their continuous equivalents.

[Table 1.7 about here]

In Table 1.8, we report the results for pollution intensive firms and non-pollution intensive firms. Specification (2) shows that determinants of eco-innovation differ slightly between two groups of firms. For polluters we find that external R&D cooperation remains an important driver of eco-innovation and confirms that abatement intensity as a positive and significant impact on the promotion of eco-innovation. Nevertheless, the impact of abatement cost on eco-innovation is slightly smaller for polluters comparing to our baseline model. Thus, the presence of abatement costs motivates pollution intensive firms to undertake eco-innovation, but as they are already likely to be highly regulated may make them less sensitive to abatement rises. In other results we find that none of TFP, size or the implementation of a EMS has as impact on the level of investment environmental R&D of pollution intensive firms. The EMS result may be due to the fact that polluters already have a relatively high rate of EMS implementation (shown in in Figure 1.6). Interestingly, we now find that pollution intensive firms that export are more likely to eco-innovate.

For the relatively cleaner firms, model (3) shows generally similar results to the full sample. Our results show that lagged abatement cost remains significant in affecting the investment in environmental R&D of firms in clean sectors. Compared with polluters, the marginal effect of our abatement cost variable is relatively larger such that 1% increase from mean in abatement intensity increases the expenditure on eco-innovation by 7 percentage point on average. However, from Table 1.2, we observe the average abatement intensity for firms in clean sectors is almost one third smaller that that of polluters. Hence, our results suggest that clean firms are more sensitive to environmental regulations. Relating our results to the pollution haven hypothesis, Gray and Shadbegian (1998) suggests that more stringent regulations may divert investment from productivity to abatement expenditure.

Our results suggest that firms in pollution intensive sectors would refer to pay the abatement costs rather than starting the eco-innovation process with its attendant costs and inherent uncertainty. In other results we find that firm age is negatively associated with eco-innovation expenditure and suggests that younger firms invest relatively more resources on eco-innovation everything else equal. We also find a positive and significant effect of lagged TFP on eco-innovation which indicates that within those relatively cleaner sectors, more productive firms invest more in eco-innovation activities.

[Table 1.8 about here]

1.5 Robustness Checks

As part of our analysis we undertake a series of sensitivity checks. The first set of robustness checks test whether using different plant to firm level aggregation strategies influences the results. For example, our results may be biased if we only have data on a small number of a firm's plants which would underestimate certain key variables. To address potential aggregation bias we restrict the sample to firms according to the ratio between the firms′ total number of full-time equivalent employees for plants from the ANTIPOL data and the total number of full-time equivalent employees from the financial data sets (FICUS and FARE). A ratio equal to 100% suggests that there is no measurement error. In our estimations we try three alternative thresholds that reduce measurement error as the threshold increases but reduces the sample as the threshold increases.

Table 1.9 presents our results from equation (1) using different thresholds for aggregating plants to firms. Column (1) reports the baseline estimation with the whole sample which can also be referred as 0% threshold, Columns (2), (3) and (4) reports the results for thresholds of 50%, 75% and 90%, respectively. Focusing on our key variables of external R&D and abatement intensity, our results are fairly consistent across the different models. Following the same approach, we re-estimate the equation (1) using our three different external R&D cooperation dummies and results are presented in Table 1.10. We also find consistent results comparing with Table 1.7.

[Table 1.9 about here]

[Table 1.10 about here]

There are two possible reasons for the differences in the results. First, the measurement bias is reduced as we restrict the sample. Second, the composition of sample changes as the threshold increases. This selection may be endogenous as, for example, firms in pollution intensive sectors are those most likely to be included in the 90% threshold sample as even their smallest plants have to answer to ANTIPOL survey which a number of plants in clean sectors do not. Despite these differences the results are fairly robust to the choice of threshold and all of the key variables are significantly different from zero for all thresholds suggesting that higher thresholds reduce the potential bias from the aggregation process.

Table 1.11 reports the distribution of firms by sectors for the 0% threshold sample and the 90% threshold sample. From Table 1.11 we observe that there is no substantial difference in the composition of the sample between these two groups. Hence, we are confident that the effect of a different sample composition is very small in our case and that our main results are not unduly influenced by our aggregation methodology from plant level to firm level.

[Table 1.11 about here]

Secondly, we implement Probit estimation to assess the impact of determinants on the probability of doing eco-innovation. We generate an eco-innovation status variable which equals to one if eco-innovation is greater than zero, zero other wise. Table 1.12 presents results on Probit estimations. In Model (1) We find that compare to firms that had not previously cooperated with external partners in R&D, firms that cooperated in the previous period have 3.8% higher probability to devote to eco-innovation. Particularly in Model (2), cooperating with foreign partners shows a significant and positive effect on the probability of devoting to eco-innovation whereas cooperating with other two types of external partners does not. Regarding control variables, larger and more productive firms are more likely to invest in eco-innovation. In Model (4), we apply the generalized estimating equations (GEE) estimation since calculating marginal effect for interaction term in Probit estimation is inefficient (Papke and Wooldridge, 2008). We find the interaction term between external R&D cooperation and internal R&D remains insignificant which also confirms our previous finding. Overall the results are fairly consistent comparing with Tobit estimates, showing the robustness of our results.

[Table 1.12 about here]

In a final robustness check we use two alternative TFP measures using the Levinsohn and Petrin (2003) approach and Wooldridge (2009) approach to test whether excluding R&D expenditure from the TFP estimation alters our results. To tackle the endogeneity problems faced by traditional solutions, Levinsohn and Petrin (2003) propose a two step approach based on using material and investment respectively to proxy for the firm's unobserved productivity. Furthermore, Wooldridge (2009) argues that traditional two-stage methods such as Olley and Pakes (1996) and Levinsohn and Petrin (2003) are not efficient and require constructing the standard errors by bootstrap. Wooldridge (2009) proposes a new approach combining the moment conditions of both stages into a single set and obtains efficient GMM estimates in one step. The correlation coefficients between these measurements of TFP are relatively high and Table 1.13 shows that the estimated MEs vary from 0.0511 to 0.0550 and remain significant at the 5% level across the three different specifications.

[Table 1.13 about here]

1.6 Conclusions

This study contributes to the empirical literature that examines the drivers of eco-innovation with particular attention being given to the impact of outsourcing R&D on the expenditure on eco-innovation. Identifying the determinants of eco-innovation is of interest since advances in environmental technologies are thought to help in the fight against the effects of climate change. Although R&D expenditure has often been studied, previous data limitations have restricted the ability to analyze the determinants of eco-innovation. In this chapter we are able to overcome the data limitations of earlier studies by constructing a panel of 2,197 French firms for the period 2004-2011 using data from various surveys on innovation, environmental activities and finance.

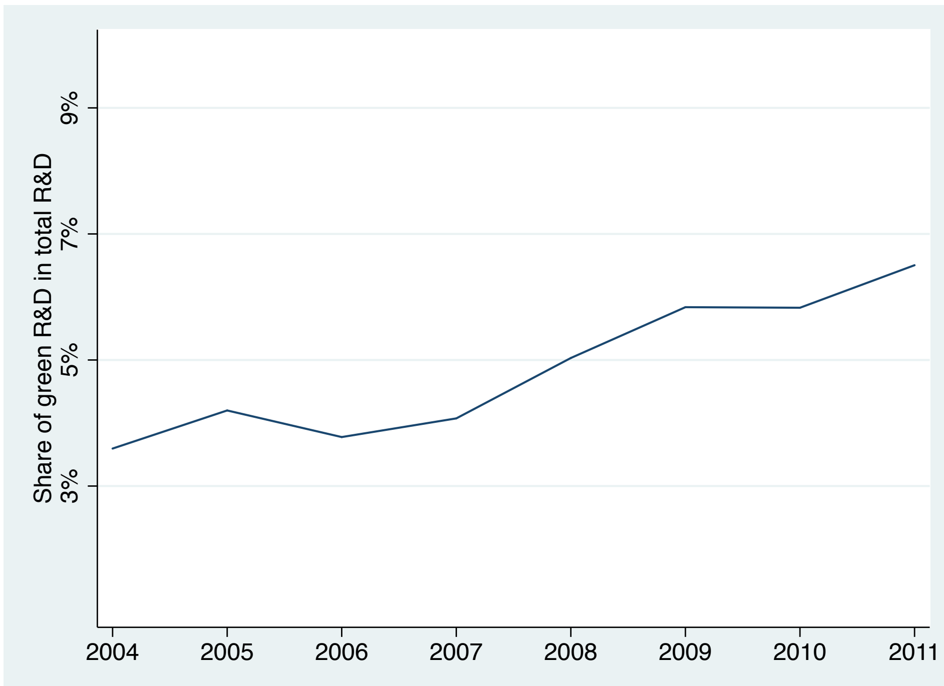
Theoretically, we separate the determinants of eco-innovation into those that capture market pull, technology push and regulation pull/push. From this theoretical framework we formulate five hypotheses to reflect the impact of firms characteristics and policy instruments on eco-innovation expenditure. These hypotheses are tested on a unique panel data of firms across 22 manufacturing sectors in France taking into account various firm heterogeneity and endogeneity concerns.

Our main finding is that there is a positive effect of external knowledge sourcing on eco-innovation expenditure and that this is primarily driven by cooperating with foreign partners. The result holds for both pollution intensive and non pollution intensive firms, however the magnitude of the effect on pollution intensive is a little lower. Another of our main findings is that the stringency of regulations has a positive effect on the level of eco-innovation. The policy that promotes eco-innovation reduces technological and market uncertainty, on the other hand, given that eco-innovations are affected by the effect of double externalities, implementation of environmental regulation helps fostering eco-innovation. Although command and control (COC) instruments are significantly effective in promoting eco-innovation, the lack of market-based policy instruments limits the development of eco-innovation in the French context.

Our empirical results provide further explanation of the drivers that initiate and improve eco-innovations and carries some important policy implementations. Whilst organizational capabilities are key drivers of eco-innovation, the existence of strict government policies is essential in stimulating the degree of eco-innovation. Thus, current environmental regulations that target on promoting eco-innovations need to be supported by well designed policy mixes for pollution abatement which should be inclusive of different kinds of policy instruments. Also government supported innovation networks are also important through which innovative firms can get the necessary support to enhance their organizational capabilities. Overall, with the existence of sector heterogeneity, eco-innovation requires more support from well designed and targeted environmental regulations. Evidence presented suggests that current regulatory framework does not seem to effectively motivate eco-innovation, especially for market-based environmental policy instruments. Thus, current regulatory instruments require enhancement and policymakers should provide incentives to firms to engage in eco-innovation by using a mixture of different kinds of policy.

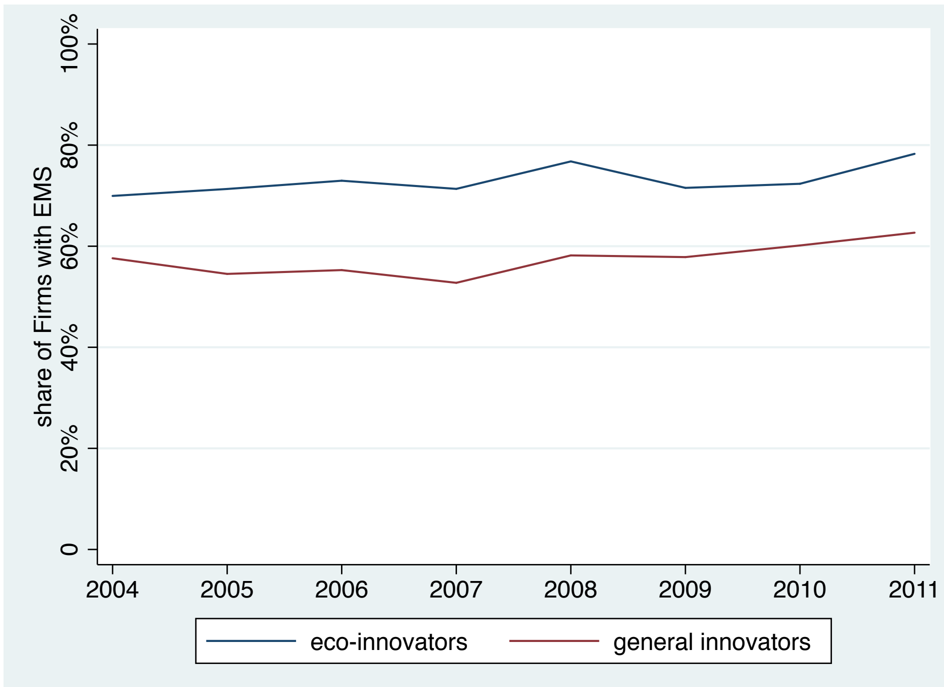
1.7 Figures and tables

Figure 1.1: Annual average environmental R&D



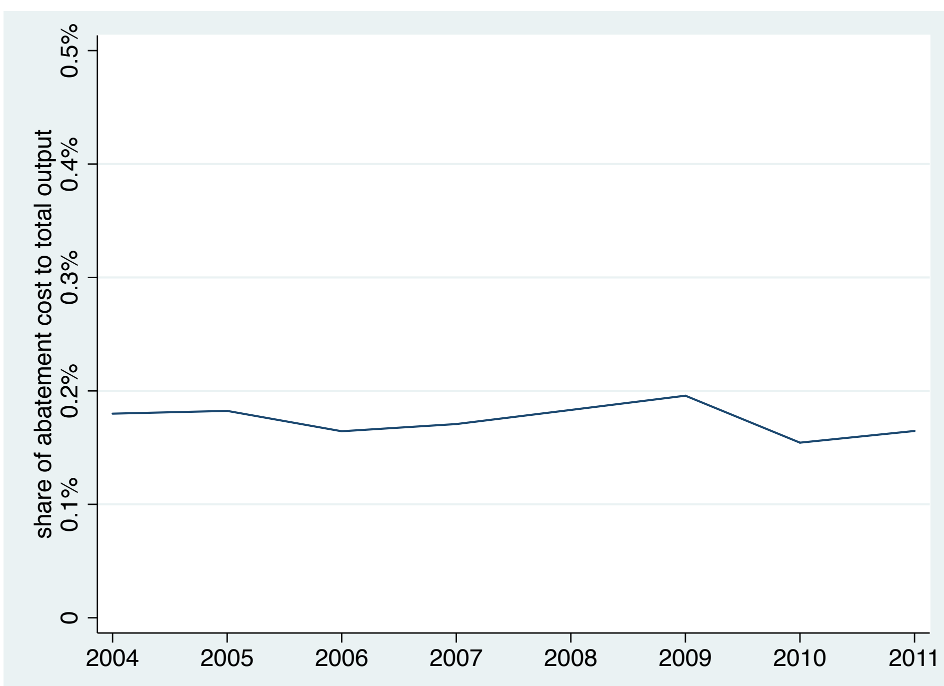
Source: elaboration based on the Annual Survey on the Resources Devoted to R&D Activities data on French firms over the period 2004-2011.

Figure 1.2: Firms with EMS and other management systems



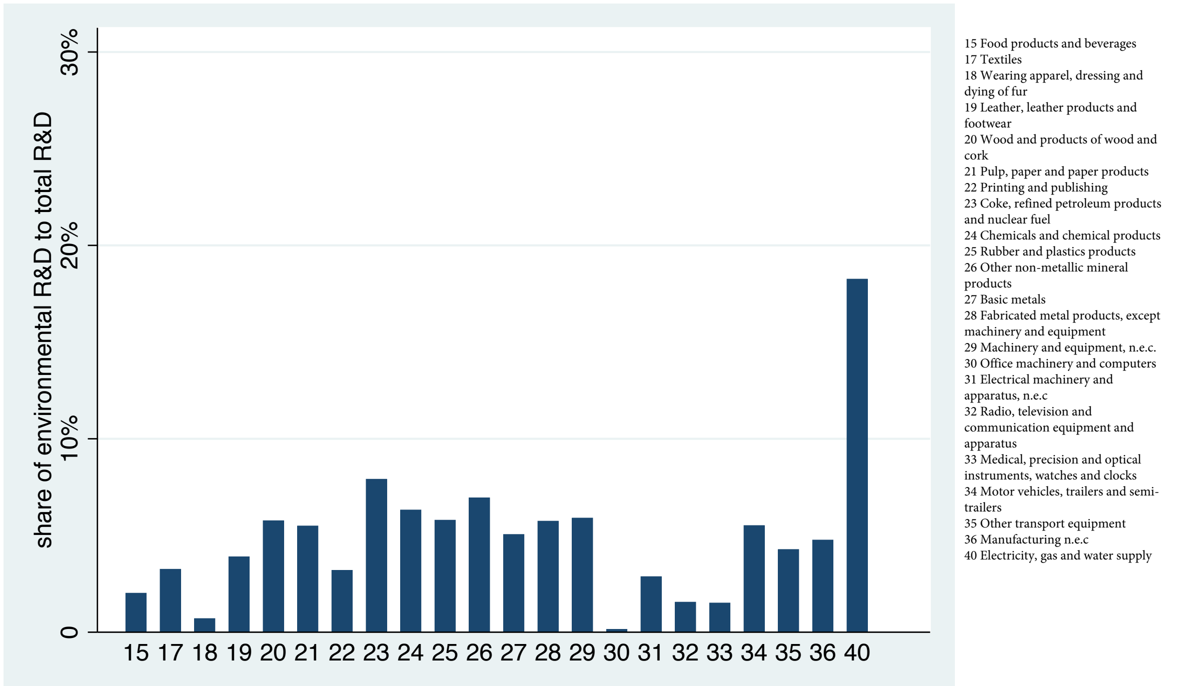
Source: elaboration based on ANTIPOL data on French firms over the period 2004-2011.

Figure 1.3: Annual average abatement cost intensity



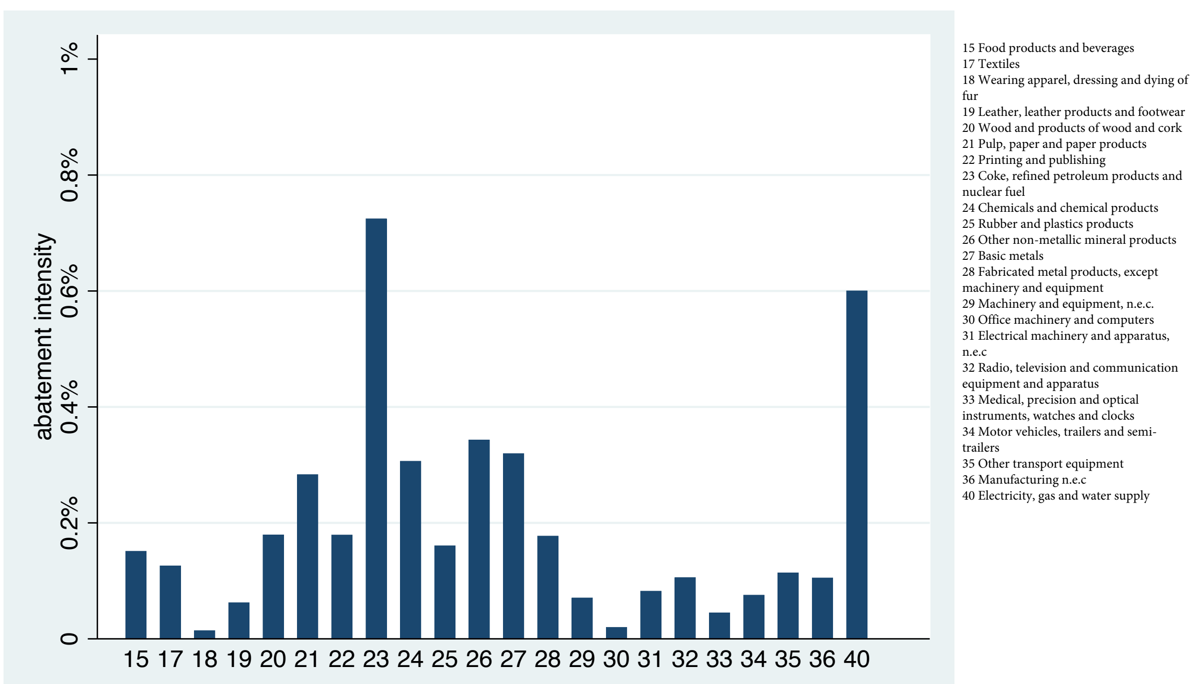
Source: elaboration based on ANTIPOL data on French firms over the period 2004-2011.

Figure 1.4: Average environmental R&D intensity



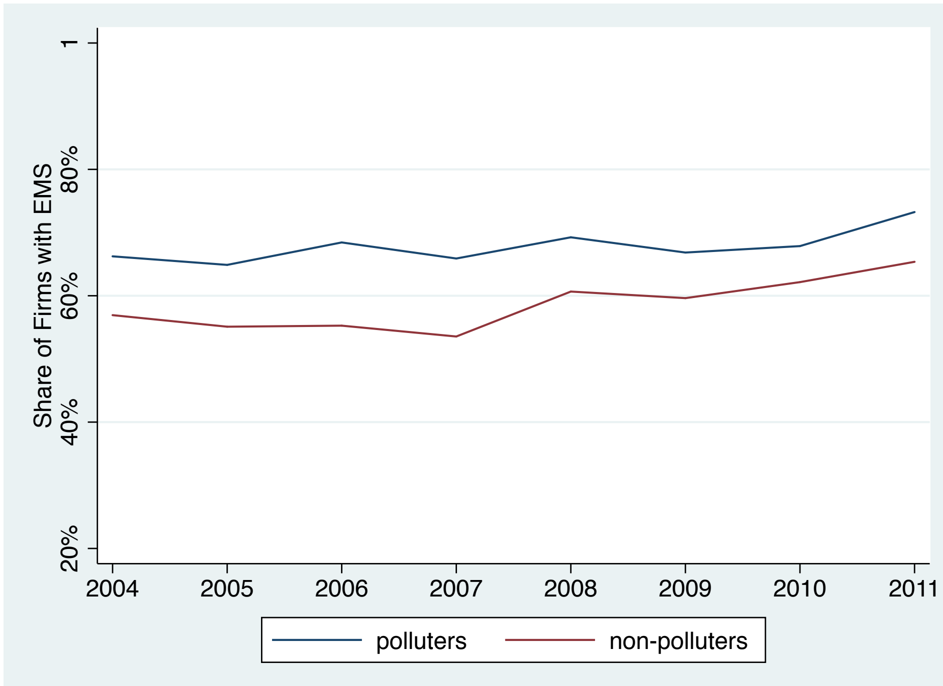
Source: elaboration based on the Annual Survey on the Resources Devoted to R&D Activities data on French firms over the period 2004-2011.

Figure 1.5: Average share of abatement cost to total output



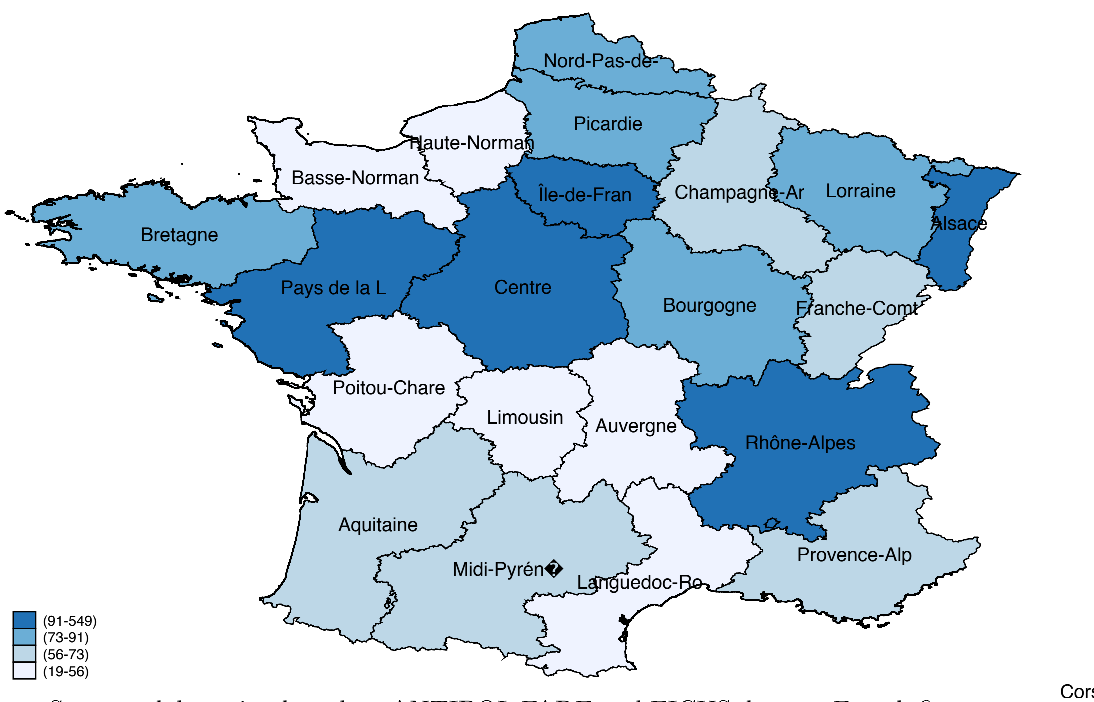
Source: elaboration based on ANTIPOL,FARE and FICUS data on French firms over the period 2004-2011.

Figure 1.6: Firms with EMS and other management systems



Source: elaboration based on ANTIPOL data on French firms over the period 2004-2011.

Figure 1.7: Spatial distribution of firms



Source: elaboration based on ANTIPOL,FARE and FICUS data on French firms over the period 2004-2011.

Table 1.1: Definition of variables

Variable	Description
Dependent Variables	
Log EnvR&D	log of green R&D expenditure
Explanatory variables	
ExtR&D_d	=1 if the firm is subcontracting and collaborating on R&D with external parties, 0 otherwise
ExtR&D_foreign_d	=1 if the firm is subcontracting and collaborating on R&D with overseas private sector, 0 otherwise
ExtR&D_domestic_d	=1 if the firm is subcontracting and collaborating on R&D with private sector in France, 0 otherwise
ExtR&D_public_d	=1 if the firm is subcontracting and collaborating on R&D with public sectors (including higher educations and public organizations), 0 otherwise
Log_ExtR&D	log of R&D investment subcontract and collaborate with external parties,
Log_ExtR&D_foreign	log of R&D investment subcontract and collaborate with overseas private sector
Log_ExtR&D_domestic	log of R&D investment subcontract and collaborate with with private sector in France
Log_ExtR&D_public	log of R&D investment subcontract and collaborate with public sectors (including higher educations and public organizations)
R&D_intensity	number of full-time equivalent employees dedicated to R&D divided by total number of full-time equivalent employees
EMS	=1 if the firm has implemented ISO14001 or other environmental management systems, 0 otherwise
EMS_process	=1 if the firm is in the process of applying for environment management system, 0 otherwise
Abatement_intensity	total abatement costs divided by total output in %
Pubfunding_d	=1 if the firm receives resources from public sector
TFP	total factor productivity
Log_age	log of number of years since the firm began to operate
Log_size	log of firm size (total number of full-time equivalent employees)
Log_avewage	log of average wage (total salary expenditure divided by total number of full-time equivalent employees)
Export_d	=1 if the firm exports, 0 otherwise
French_group	=1 if more than 50% of share of the firm is held by a French group, 0 otherwise
Foreign_group	=1 if more than 50% of share of the firm is held by a foreign group, 0 otherwise
Leverage	ratio between total liability and shareholders' equity

Table 1.2: Summary statistics for all firms

Variable	Mean	Std.Dev	Min	Max
EnvR&D_d	0.2661	0.4419	0	1
EnvR&D (EUR th.)	442.9893	4626.066	0	191780.4
ExtR&D_d	0.6027	0.4894	0	1
ExtR&D_foreign_d	0.1956	0.3967	0	1
ExtR&D_domestic_d	0.4892	0.4999	0	1
ExtR&D_public_d	0.2766	0.4473	0	1
ExtR&D (EUR th.)	2201.823	11278.52	0	287914
ExtRD_foreign (EUR th.)	596.7932	3864.092	0	82708.79
ExtRD_domestic (EUR th.)	1433.073	8916.767	0	263279
ExtRD_public (EUR th.)	163.9508	1937.113	0	62508
R&D_intensity	0.0880	0.0974	0.0002	0.8421
EMS	0.7158	0.4511	0	1
EMS process	0.1236	0.3291	0	1
Abatement_intensity (in %)	0.1760	0.3782	0	2.5846
Pubfunding_d	0.2516	0.4339	0	1
TFP	3.3442	0.4599	0.1250	7.0755
Age	33.3045	23.5128	2	111
Size	604.7061	805.8915	12.5	3908
Avewage (EUR th.)	38.2415	11.5514	17.6686	88.5162
Export_d	0.9557	0.2058	0	1
French_group	0.5229	0.4995	0	1
Foreign_group	0.4664	0.4989	0	1
Leverage	1.3793	2.8240	-11.6410	22.9539

Source: ANTIPOL, FARE, FICUS and The Annual Survey on the Resources Devoted to R&D Activities data. Unit: thousand euros. Information refers to the period 2004-2011.

Table 1.3: Annual environmental R&D expenditure for 2004-2011

year	annual average R&D	average environmental R&D
2004	7738.334	74.33994
2005	7571.642	97.91081
2006	6924.475	88.70898
2007	6707.748	88.84464
2008	6800.48	111.3661
2009	6552.904	129.9282
2010	6603.3	135.3626
2011	7916.946	173.2246

Source: The Annual Survey on the Resources Devoted to R&D Activities.
Unit: thousand euros. Information refers to the period 2004-2011.

Table 1.4: Average environmental R&D expenditure by sector

		All firms		Eco-innovators	
Nace code	Description	Number of firms	Green R&D	Number of firms	Green R&D
15	Food products and beverages	198	20.43564	35	123.7706
17	Textiles	72	31.90969	19	177.8669
18	Wearing apparel, dressing and dying of fur	9	24.11169	2	241.1169
19	Leather, leather products and footwear	12	15.09229	3	61.87838
20	Wood and products of wood and cork	23	37.42039	9	111.0541
21	**Pulp, paper and paper products**	43	116.6858	18	286.5966
22	Printing and publishing	9	12.09498	2	75.59361
23	**Coke, refined petroleum products and nuclear fuel**	13	282.8591	9	593.0917
24	**Chemicals and chemical products**	379	466.2922	158	1703.992
25	Rubber and plastics products	202	93.10162	84	337.252
26	**Other non-metallic mineral products**	67	684.9005	29	1897.066
27	**Basic metals**	78	144.1542	28	562.2012
28	Fabricated metal products, except machinery and equipment	197	75.34621	67	275.9001
29	Machinery and equipment, n.e.c.	317	193.2221	124	664.7382
30	Office machinery and computers	12	3.605098	1	38.7548
31	Electrical machinery and apparatus, n.e.c	144	174.4865	51	708.79
32	Radio, television and communication equipment and apparatus	81	58.12385	14	471.1742
33	Medical, precision and optical instruments, watches and clocks	147	89.61187	24	815.8171
34	Motor vehicles, trailers and semi-trailers	94	496.7682	26	2856.417
35	Other transport equipment	52	4049.935	23	11413.45
36	Manufacturing n.e.c	54	707.73	22	2344.356
40	Electricity, gas and water supply	10	9338.456	7	14785.89

Source: The Annual Survey on the Resources Devoted to R&D Activities. Information refers to the period 2004-2011.

Table 1.5: Summary statistics of polluters and non-polluters

Variable	all firms	polluter	nonpolluters
EnvR&D_d	0.2659	0.3080	0.2508
	(0.4418)	(0.4618)	(0.4335)
EnvR&D (EUR th.)	442.9893	492.8611	422.0024
	(4626.006)	3732.59	(4954.4)
ExtR&D_d	0.5985	0.6622	0.5776
	(0.4902)	(0.4731)	(0.4939)
ExtR&D_foreign_d	0.1944	0.2390	0.1773
	(0.3958)	(0.4266)	(0.3819)
ExtR&D_domestic_d	0.4858	0.5368	0.4692
	(0.4998)	(0.4988)	(0.4991)
ExtR&D_public_d	0.2744	0.3835	0.2315
	(0.4462)	(0.4864)	(0.4207)
ExtR&D (EUR th.)	0.3984	0.1261	0.0872
	(0.3602)	(0.1902)	(0.1446)
ExtRD_foreign (EUR th.)	596.7932	680.32	549.35
	(3864.09)	(4257.12)	(3583.81)
ExtRD_domestic (EUR th.)	1433.073	786.43	1644.98
	(8916.767)	(3295.31)	(9957.06)
ExtRD_public (EUR th.)	163.9508	225.74	135.59
	(1937.11)	(2482.28)	(1608.57)
R&D_intensity	0.880	0.0914	0.0866
	(0.1867)	(0.0907)	(0.1001)
EMS	0.7149	0.7370	0.7059
	(0.4515)	(0.4403)	(0.4557)
EMS_process	0.1235	0.1300	0.1206
	(0.3291)	(0.3364)	(0.3257)
Abatement_intensity (in %)	0.2964	0.3281	0.1069
	(0.1967)	(0.5399)	(0.2456)
Pubfunding_d	0.2496	0.2433	0.2551
	(0.4328)	(0.4292)	(0.4359)
TFP	3.3441	3.3815	3.3285
	(0.4603)	(0.4912)	(0.4453)
Age	33.3281	34.7973	32.6753
	(23.5056)	(24.8948)	(22.8788)
Size	601.3407	554.363	625.8715
	(802.695)	(759.051)	(823.9445)
Avewage (EUR th.)	38.2013	40.5277	37.2803
	(11.5479)	(10.9773)	(11.6523)
Export_d	0.9556	0.9487	0.9586
	(0.2059)	(0.2207)	(0.1992)
French_group	0.5221	0.5051	0.5313
	(0.4995)	(0.5001)	(0.4991)
Foreign_group	0.4673	0.4813	0.4602
	(0.4989)	(0.4998)	(0.4985)
Leverage	1.3864	1.2832	1.4198
	(2.8287)	(2.7124)	(2.8681)

Source: ANTIPOL, FARE, FICUS and The Annual Survey on the Resources Devoted to R&D Activities data. Standard deviations in parentheses. Information refers to the period 2004-2011.

Table 1.6: Determinants of eco-innovation of French manufacturing firms (2004-2011): baseline estimation

	Dependent variable: Log_EnvR&D			
	(Model 1) Tobit	(Model 2) Tobit	(Model 3) Tobit	(Model 4) (Tobit)
ExtR&D_d$_{i(t-1)}$	0.0670***		0.0669***	0.1311***
	(0.0191)		(0.0191)	(0.0488)
ExtR&D_foreign_d$_{i(t-1)}$		0.0550**		
		(0.0223)		
ExtR&D_domestic_d$_{i(t-1)}$		0.0196		
		(0.0182)		
ExtR&D_public_d$_{i(t-1)}$		0.0305		
		(0.0198)		
rd_intensity$_{i(t-1)}$	-0.0104	-0.0290		-0.1475
	(0.1581)	(0.1585)		(0.4121)
ExtR&D*R&D_intensity$_{i(t-1)}$				0.1111
				(0.4205)
EMS$_{i(t-1)}$	0.0644***	0.0669***	0.0644***	0.1408***
	(0.0225)	(0.0224)	(0.0224)	(0.0475)
EMS_process$_{i(t-1)}$	0.0073	0.0076	0.0073	0.0102
	(0.0217)	(0.0217)	(0.0217)	(0.0435)
Abatement_intensity$_{i(t-1)}$	0.0620***	0.0640***	0.0619***	0.1165**
	(0.0201)	(0.0201)	(0.0201)	(0.0422)
Pubfunding_d$_{i(t-1)}$	0.0319	0.0308	0.0316	0.0364
	(0.0203)	(0.0204)	(0.0202)	(0.0424)
TFP$_{i(t-1)}$	0.0511**	0.0504**	0.0514**	0.1004**
	(0.0243)	(0.0242)	(0.0243)	(0.0478)
Log_age$_{i(t-1)}$	-0.0327	-0.0325	-0.0322	-0.0288
	(0.0206)	(0.0206)	(0.0206)	(0.0359)
Log_size$_{i(t-1)}$	0.0777***	0.0745***	0.0773***	0.1003***
	(0.0151)	(0.0152)	(0.0151)	(0.0262)
Log_avewage$_{i(t-1)}$	0.0098	0.0110	0.0051	-0.0069
	(0.0562)	(0.0560)	(0.0544)	(0.1075)
Export_d$_{i(t-1)}$	0.0614	0.0619	0.0610	0.0979
	(0.0492)	(0.0491)	(0.0491)	(0.0797)
French_group$_{i(t-1)}$	0.0827	0.0801	0.0824	0.1749
	(0.0949)	(0.0947)	(0.0948)	(0.1596)
Foreign_group$_{i(t-1)}$	0.0654	0.0594	0.0659	0.1338
	(0.0962)	(0.0959)	(0.0960)	(0.1598)
Leverage$_{i(t-1)}$	-0.0031	-0.0029	-0.0031	-0.0058
	(0.0026)	(0.0026)	(0.0026)	(0.0050)
Log likelihood	-7580.96	-7581.17	-7582.23	-7580.82
Wald chi2	323.68***	323.64***	322.90***	324.12***
Observations	7,238	7,238	7,243	7,238
No.firms	2,197	2,197	2,199	2,197

Marginal effects reported with standard errors in parentheses for Specification (1), (2) and (3). Coefficient reported with standard errors in parentheses for Specification (4). All regressions include sectoral, year and regional dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7: Determinants of eco-innovation of French manufacturing firms (2004-2011): alternative measurement of external R&D

	Dependent variable: Log_EnvR&D			
	(Model 1) Tobit	(Model 2) Tobit	(Model 3) Tobit	(Model 4) (Tobit)
Log_ExtR&D$_{i(t-1)}$	0.0104***		0.0095***	0.1828***
	(0.0036)		(0.0035)	(0.0491)
Log_ExtR&D_foreign$_{i(t-1)}$		0.0075**		
		(0.0042)		
Log_ExtR&D_domestic$_{i(t-1)}$		0.0022		
		(0.0036)		
Log_ExtR&D_public$_{i(t-1)}$		0.0064		
		(0.0052)		
R&D_intensity$_{i(t-1)}$	-0.0215	-0.0362		0.8688
	(0.1586)	(0.1599)		(0.6287)
ExtR&D*R&D_intensity$_{i(t-1)}$				-0.8075
				(0.5197)
EMS$_{i(t-1)}$	0.0664***	0.0663***	0.0645***	0.6959***
	(0.0223)	(0.0224)	(0.0223)	(0.2429)
EMS_process$_{i(t-1)}$	0.0091	0.0067	0.0061	0.0064
	(0.0216)	(0.0216)	(0.0216)	(0.0372)
Abatement_intensity$_{i(t-1)}$	0.0598***	0.0634***	0.0614***	0.0673**
	(0.0199)	(0.0200)	(0.0199)	(0.0214)
Pubfunding_d$_{i(t-1)}$	0.0315	0.0318	0.0327	0.0377
	(0.0202)	(0.0205)	(0.0201)	(0.0223)
TFP$_{i(t-1)}$	0.0602**	0.0518**	0.0509**	0.0539**
	(0.0240)	(0.0242)	(0.0241)	(0.0265)
Log_age$_{i(t-1)}$	-0.0342*	-0.0325	-0.0321	-0.0356
	(0.0205)	(0.0206)	(0.0206)	(0.0226)
Log_size$_{i(t-1)}$	0.0742***	0.0733***	0.0728***	0.0413***
	(0.0153)	(0.0155)	(0.0153)	(0.0162)
Log_avewage$_{i(t-1)}$	-0.0056	0.0076	0.0010	-0.0009
	(0.0559)	(0.0559)	(0.0544)	(0.0614)
Export_d$_{i(t-1)}$	0.0605	0.0601	0.0596	0.0657
	(0.0488)	(0.0489)	(0.0489)	(0.0537)
french_group$_{i(t-1)}$	0.0767	0.0809	0.0803	0.0915
	(0.0944)	(0.0944)	(0.0943)	(0.1034)
foreign_group$_{i(t-1)}$	0.0579	0.0615	0.0645	0.0739
	(0.0962)	(0.0957)	(0.0955)	(0.1046)
Leverage$_{i(t-1)}$	-0.0031	-0.0031	-0.0032	-0.0058
	(0.0026)	(0.0026)	(0.0026)	(0.0050)
log likelihood	-7580.96	-7584.16	-7584.78	-7580.24
Wald chi2	323.68***	317.17***	318.00***	325.32***
Observations	7,238	7,238	7,243	7,238
No.firms	2,197	2,197	2,199	2,197

Marginal effects reported with standard errors in parentheses for Specification (1), (2) and (3). Coefficient reported with standard errors in parentheses for Specification (4). All regressions include sectoral, year and regional dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.8: Determinants of eco-innovation of French manufacturing firms (2004-2011): pollution intensive and non-pollution intensive firms

	Dependent variable: Log_EnvR&D		
	(Model 1) (all firms) Tobit	(Model 2) (polluters) Tobit	(Model 3) (non-polluters) Tobit
ExtR&D_d$_{i(t-1)}$	0.0670***	0.0716**	0.0642***
	(0.0191)	(0.0357)	(0.0231)
R&D_intensity$_{i(t-1)}$	-0.0104	0.3201	-0.1636
	(0.1581)	(0.2791)	(0.2007)
EMS$_{i(t-1)}$	0.0644***	0.0505	0.0765***
	(0.0225)	(0.0387)	(0.0282)
EMS_process$_{i(t-1)}$	0.0073	-0.0307	0.0269
	(0.0217)	(0.0387)	(0.0267)
Abatement_intensity$_{i(t-1)}$	0.0620***	0.0569**	0.0746**
	(0.0201)	(0.0269)	(0.0323)
Pubfunding_d$_{i(t-1)}$	0.0319	-0.0079	0.0552**
	(0.0203)	(0.0345)	(0.0257)
TFP$_{i(t-1)}$	0.0511**	0.0133	0.0688**
	(0.0243)	(0.0427)	(0.0305)
Log_age$_{i(t-1)}$	-0.0327	0.0343	-0.0566**
	(0.0206)	(0.0399)	(0.0247)
Log_size$_{i(t-1)}$	0.0777***	0.0325	0.0980***
	(0.0151)	(0.0272)	(0.0189)
Log_avewage$_{i(t-1)}$	0.0098	0.0697	-0.0345
	(0.0562)	(0.0997)	(0.0698)
Export_d$_{i(t-1)}$	0.0614	0.1919**	-0.0174
	(0.0492)	(0.0854)	(0.0621)
French_group$_{i(t-1)}$	0.0827	-0.0158	0.1777
	(0.0949)	(0.1436)	(0.1369)
Foreign_group$_{i(t-1)}$	0.0654	-0.1279	0.2102
	(0.0962)	(0.1454)	(0.1387)
Leverage$_{i(t-1)}$	-0.0031	-0.0042	-0.0029
	(0.0026)	(0.0055)	(0.0031)
Log likelihood	-7580.96	-2475.05	-5074.38
Wald chi2	323.68***	108.48***	248.53***
Observations	7,238	2,146	5,092
No.firms	2,197	577	1,620

Marginal effects reported with standard errors in parentheses. All regressions include sectoral, year and regional dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.9: Determinants of eco-innovation of French manufacturing firms (2004-2011): baseline model for different thresholds regarding aggregation process

	Dependent variable: Log_EnvR&D			
	(Model 1) (0%) Tobit	(Model 2) (50%) Tobit	(Model 3) (75%) Tobit	(Model 4) (90%) Tobit
ExtR&D_d$_{i(t-1)}$	0.0670***	0.0689***	0.0724***	0.0624**
	(0.0191)	(0.0210)	(0.0226)	(0.0250)
R&D_intensity$_{i(t-1)}$	-0.0104	-0.0752	-0.1675	-0.1647
	(0.1581)	(0.1709)	(0.1818)	(0.1931)
EMS$_{i(t-1)}$	0.0644***	0.0651***	0.0649**	0.0774***
	(0.0225)	(0.0248)	(0.0265)	(0.0285)
EMS_process$_{i(t-1)}$	0.0073	0.0004	-0.0085	-0.0118
	(0.0217)	(0.0245)	(0.0268)	(0.0298)
Abatement_intensity$_{i(t-1)}$	0.0620***	0.0607***	0.0557**	0.0516**
	(0.0201)	(0.0215)	(0.0228)	(0.0253)
Pubfunding_d$_{i(t-1)}$	0.0319	0.0315	0.0438	0.0592**
	(0.0203)	(0.0225)	(0.0245)	(0.0276)
TFP$_{i(t-1)}$	0.0511**	0.0483**	0.0556**	0.0652**
	(0.0243)	(0.0265)	(0.0283)	(0.0314)
Log_age$_{i(t-1)}$	-0.0327	-0.0249	-0.0219	-0.0214
	(0.0206)	(0.0219)	(0.0231)	(0.0243)
Log_size$_{i(t-1)}$	0.0777***	0.0792***	0.0808***	0.0857***
	(0.0151)	(0.0162)	(0.0172)	(0.0184)
Log_avewage$_{i(t-1)}$	0.0098	0.0284	0.0289	-0.0201
	(0.0562)	(0.0621)	(0.0674)	(0.0751)
Export_d$_{i(t-1)}$	0.0614	0.0368	0.0300	0.0458
	(0.0492)	(0.0529)	(0.0540)	(0.0587)
French_group$_{i(t-1)}$	0.0827	0.1018	0.1100	0.1427
	(0.0949)	(0.1033)	(0.1069)	(0.1117)
Foreign_group$_{i(t-1)}$	0.0654	0.0915	0.0955	0.1307
	(0.0962)	(0.1045)	(0.1082)	(0.1132)
Leverage$_{i(t-1)}$	-0.0031	-0.0039	-0.0040	-0.0037
	(0.0026)	(0.0029)	(0.0030)	(0.0034)
Log likelihood	-7580.96	-6729.71	-5869.39	-5146.09
LR test	323.68***	289.73***	262.83***	227.24***
Observations	7,238	6,358	5,615	4,931
No.firms	2,197	2,096	1,979	1,858

Marginal effects reported with standard errors in parentheses. All regressions include sectoral, year and regional dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.10: Determminants of eco-innovation of French manufacturing firms (2004-2011): baseline model for different thresholds regarding aggregation process

	Dependent variable: Log_EnvR&D			
	(Model 1) (0%) Tobit	(Model 2) (50%) Tobit	(Model 3) (75%) Tobit	(Model 4) (90%) Tobit
ExtR&D_foreign_d$_{i(t-1)}$	0.0550**	0.0417*	0.0504*	0.0451*
	(0.0223)	(0.0247)	(0.0268)	(0.0277)
ExtR&D_domestic_d$_{i(t-1)}$	0.0196	0.0318	0.0406*	0.0309
	(0.0182)	(0.0201)	(0.0214)	(0.0236)
ExtR&D_public_d$_{i(t-1)}$	0.0305	0.0281	0.0254	0.0377
	(0.0198)	(0.0216)	(0.0234)	(0.0261)
R&D_intensity$_{i(t-1)}$	-0.0290	-0.0886	-0.1870	-0.1867
	(0.1585)	(0.1714)	(0.1822)	(0.1936)
EMS$_{i(t-1)}$	0.0669***	0.0674***	0.0676***	0.0797***
	(0.0224)	(0.0248)	(0.0264)	(0.0285)
EMS_process$_{i(t-1)}$	0.0076	0.0003	-0.0078	-0.0109
	(0.0217)	(0.0244)	(0.0267)	(0.0297)
Abatement_intensity$_{i(t-1)}$	0.0640***	0.0625***	0.0568**	0.0531**
	(0.0201)	(0.0214)	(0.0227)	(0.0252)
Pubfunding_d$_{i(t-1)}$	0.0308	0.0304	0.0420*	0.0557**
	(0.0204)	(0.0226)	(0.0246)	(0.0277)
TFP$_{i(t-1)}$	0.0504**	0.0480**	0.0549*	0.0652**
	(0.0242)	(0.0265)	(0.0283)	(0.0314)
Log_age$_{i(t-1)}$	-0.0325	-0.0248	-0.0219	-0.0209
	(0.0206)	(0.0219)	(0.0231)	(0.0243)
Log_size$_{i(t-1)}$	0.0745***	0.0766***	0.0774***	0.0820***
	(0.0152)	(0.0163)	(0.0173)	(0.0185)
Log_avewage$_{i(t-1)}$	0.0110	0.0295	0.0295	-0.0225
	(0.0560)	(0.0619)	(0.0672)	(0.0749)
Export_d$_{i(t-1)}$	0.0619	0.0375	0.0309	0.0464
	(0.0491)	(0.0528)	(0.0539)	(0.0586)
French_group$_{i(t-1)}$	0.0801	0.1007	0.1092	0.1425
	(0.0947)	(0.1031)	(0.1067)	(0.1115)
Foreign_group$_{i(t-1)}$	0.0594	0.0878	0.0917	0.1279
	(0.0959)	(0.1042)	(0.1079)	(0.1130)
Leverage$_{i(t-1)}$	-0.0029	-0.0039	-0.0039	-0.0036
	(0.0026)	(0.0029)	(0.0030)	(0.0034)
Log likelihood	-7581.17	-6730.72	-5869.39	-5145.39
LR test	323.38***	287.91***	262.83***	228.35***
Observations	7,238	6,358	5,615	4,931
No.firms	2,197	2,096	1,979	1,858

Marginal effects reported with standard errors in parentheses. All regressions include sectoral, year and regional dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.11: Firm distribution for threshold 0% level and threshold 100% level

		0% threshold		100% threshold	
Nace code	Description	Number of firms	Percentage in %	Number of firms	Percentage in %
15	Food products and beverages	198	8.95	130	7.83
17	Textiles	72	3.25	59	3.58
18	Wearing apparel, dressing and dying of fur	9	0.41	3	0.18
19	Leather, leather products and footwear	12	0.54	11	0.66
20	Wood and products of wood and cork	23	1.04	21	1.31
21	Pulp, paper and paper products	43	1.94	32	1.91
22	Printing and publishing	9	0.41	7	0.42
23	Coke, refined petroleum products and nuclear fuel	13	0.59	10	0.59
24	Chemicals and chemical products	379	17.13	263	15.83
25	Rubber and plastics products	202	9.13	165	9.92
26	Other non-metallic mineral products	67	3.03	37	2.27
27	Basic metals	78	3.52	64	3.88
28	Fabricated metal products, except machinery and equipment	197	8.90	158	9.56
29	Machinery and equipment, n.e.c.	317	14.32	254	15.23
30	Office machinery and computers	12	0.54	6	0.36
31	Electrical machinery and apparatus, n.e.c	144	6.51	103	6.15
32	Radio, television and communication equipment and apparatus	81	3.66	63	3.76
33	Medical, precision and optical instruments, watches and clocks	147	6.64	106	6.39
34	Motor vehicles, trailers and semi-trailers	94	4.25	79	4.78
35	Other transport equipment	52	2.35	45	2.69
36	Manufacturing n.e.c	54	2.44	37	2.27
40	Electricity, gas and water supply	10	0.45	7	0.42
total		2,213	100	1,660	100

Source: ANTIPOL, FARE, FICUS and The Annual Survey on the Resources Devoted to R&D Activities data. Information refers to the period 2004-2011.

Table 1.12: Probability of eco-innovation of French manufacturing firms (2004-2011)

	Dependent variable: EnvR&D_d			
	(Model 1) Probit	(Model 2) Probit	(Model 3) Probit	(Model 4) (GEE)
ExtR&D_d$_{i(t-1)}$	0.0380***		0.0375***	0.1311***
	(0.0115)		(0.0115)	(0.0488)
ExtR&D_foreign_d$_{i(t-1)}$		0.0268**		
		(0.0136)		
ExtR&D_domestic_d$_{i(t-1)}$		0.0142		
		(0.0109)		
ExtR&D_public_d$_{i(t-1)}$		0.0162		
		(0.0124)		
R&D_intensity$_{i(t-1)}$	-0.0693	-0.0784		-0.1475
	(0.0924)	(0.0925)		(0.4121)
ExtR&D*IntR&D$_{i(t-1)}$				0.1111
				(0.4205)
EMS$_{i(t-1)}$	0.0431***	0.0441***	0.0432***	0.1408***
	(0.0138)	(0.0137)	(0.0137)	(0.0475)
EMS_process$_{i(t-1)}$	0.0070	0.0068	0.0070	0.0102
	(0.0132)	(0.0131)	(0.0132)	(0.0435)
Abatement_intensity$_{i(t-1)}$	0.0369***	0.0371***	0.0369***	0.1165**
	(0.0124)	(0.0123)	(0.0124)	(0.0422)
Pubfunding_d$_{i(t-1)}$	0.0107	0.0100	0.0096	0.0364
	(0.0125)	(0.0125)	(0.0124)	(0.0424)
TFP$_{i(t-1)}$	0.0343**	0.0339**	0.0344**	0.1004**
	(0.0147)	(0.0146)	(0.0147)	(0.0478)
Log_age$_{i(t-1)}$	-0.0148	-0.0148	-0.0142	-0.0288
	(0.0117)	(0.0116)	(0.0116)	(0.0359)
Log_size$_{i(t-1)}$	0.0337***	0.0323***	0.0341***	0.1003
	(0.0093)	(0.0093)	(0.0093)	(0.0262)
Log_avewage$_{i(t-1)}$	-0.0088	-0.0089	-0.0167	-0.0069
	(0.0335)	(0.0334)	(0.0325)	(0.1075)
Export_d$_{i(t-1)}$	0.0366	0.0368	0.0363	0.0979
	(0.0291)	(0.0289)	(0.0290)	(0.0797)
French_group$_{i(t-1)}$	0.0498	0.0482	0.0501	0.1749
	(0.0520)	(0.0517)	(0.0519)	(0.1596)
Foreign_group$_{i(t-1)}$	0.0406	0.0376	0.0420	0.1338
	(0.0527)	(0.0524)	(0.0526)	(0.1598)
Leverage$_{i(t-1)}$	-0.0020	-0.0020	-0.0019	-0.0058
	(0.0017)	(0.0017)	(0.0017)	(0.0050)
log likelihood	-2923.22	-2924.18	-2924.47	
Wald chi2	260.77***	258.76***	259.85***	242.01***
observations	7,300	7,300	7,305	7,300
No.firms	2,212	2,212	2,214	2,212

Marginal effects reported with standard errors in parentheses. All regressions include sectoral, year and regional dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1.13: Determinants of eco-innovation of French manufacturing firms (2004-2011): alternative measurements of total factor productivity

	Dependent variable: Log_EnvR&D		
	(Model 1)	(Model 2)	(Model 3)
	(all firms)	(all firms)	(all firms)
	Tobit	Tobit	Tobit
ExtR&D_d$_{i(t-1)}$	0.0670***	0.0672***	0.0669***
	(0.0191)	(0.0191)	(0.0191)
R&D_intensity$_{i(t-1)}$	-0.0104	-0.0109	-0.0108
	(0.1581)	(0.1580)	(0.1581)
EMS$_{i(t-1)}$	0.0644***	0.0638***	0.0643***
	(0.0225)	(0.0224)	(0.0225)
EMS_process$_{i(t-1)}$	0.0073	0.0073	0.0072
	(0.0217)	(0.0217)	(0.0217)
Abatement_intensity$_{i(t-1)}$	0.0620***	0.0620***	0.0620***
	(0.0201)	(0.0201)	(0.0201)
Pubfunding_d$_{i(t-1)}$	0.0319	0.0322	0.0319
	(0.0203)	(0.0203)	(0.0203)
TFP$_{i(t-1)}$	0.0511**		
	(0.0243)		
TFP_lp$_{i(t-1)}$		0.0550**	
		(0.0248)	
TFP_wooldridge$_{i(t-1)}$			0.0533**
			(0.0244)
Log_age$_{i(t-1)}$	-0.0327	-0.0326	-0.0328
	(0.0206)	(0.0206)	(0.0206)
Log_size$_{i(t-1)}$	0.0777***	0.0763***	0.0767***
	(0.0151)	(0.0152)	(0.0152)
Log_avewage$_{i(t-1)}$	0.0098	0.0060	0.0072
	(0.0562)	(0.0564)	(0.0563)
Export_d$_{i(t-1)}$	0.0614	0.0612	0.0612
	(0.0492)	(0.0492)	(0.0492)
French_group$_{i(t-1)}$	0.0827	0.0819	0.0824
	(0.0949)	(0.0949)	(0.0949)
Foreign_group$_{i(t-1)}$	0.0654	0.0651	0.0649
	(0.0962)	(0.0962)	(0.0962)
Leverage$_{i(t-1)}$	-0.0031	-0.0031	-0.0031
	(0.0026)	(0.0026)	(0.0026)
Log likelihood	-7580.96	-7583.39	-7580.88
Wald chi2	323.68***	324.62***	324.02***
Observations	7,238	7,244	7,239
No.firms	2,197	2,198	2,197

Marginal effects reported with standard errors in parentheses. All regressions include sectoral, year and regional dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2

Eco-innovation, environmental regulation and firm performance: Evidence from French manufacturing firms

Abstract

In this chapter we examine the impact of environmental regulations on firm performance measured by productivity and profitability using a firm-level panel data of French manufacturing firms that invest in R&D. More specifically, we measure environmental abatement costs to capture regulatory stringency and investigate whether stringent environmental regulations weaken firms' economic performance. In addition we test whether regulatory induced eco-innovation could offset environmental abatement pressure, known as the Porter hypothesis. Finally, we provide new evidence on the relationship between regulatory stringency and profitability. Unlike studies that use more aggregated data, our unique firm-level data-set allows us to use an identification strategy that is less sensitive to macroeconomics shocks that may be correlated with country or sector level eco-innovation and environmental regulations. Our results show that at the current stage, stricter environmental regulations harm firm total factor productivity (TFP) and meanwhile eco-innovation is not able to offset this negative effect for French innovators. Meanwhile, we find regulations have no impact on firm profitability after all, whereas eco-innovation significantly reduces firm's profitability. Overall, we do not find sufficient evidence supporting the Porter hypothesis. Policy implications are discussed.

Keywords: Eco-Innovation, France, abatement costs, productivity

2.1 Introduction

Along with economic development, pollution as an accompaniment created along with economic activities has affected the environment and further intensified climate change. To handle the challenges of climate change and resource scarcity, more and more organizations have started advocating innovation activities relating to environment protection to effectively reduce pollution and improve the utilization of scarce resources (Carrillo-Hermosilla et al., 2010). Triguero et al. (2013) introduce eco-innovation as a common environmental strategy that firms adopt to achieve superior environmental and economic performance simultaneously.

As the third largest economy in the EU, France possesses a strong track record in environmental protection. The total environmental expenditures accounted for about 3% of GDP in France which is above the EU members' average and in the Eco-innovation Scoreboard, France is at the 7th place in 2015(Eco-innovation Observatory, 2018). The eco-industry employment accounts for on average 1.3% of total paid employment in France (European Commission, 2015).[1] Cainelli et al. (2011) illustrate the importance of eco-industry and suggest that eco-industry has the capability to help the world begin to recover from the financial crises.

This study investigates the direct relationship between regulatory stringency and produc-

[1] The definition for eco-industry is that Firms providing goods and services for environmental protection. The definition includes the provision of clean technologies, renewable energy, waste recycling, nature and landscape protection, and ecological renovation of urban areas.(European Commission, 2018)

tivity, and the consequent indirect influence of eco-innovation triggered by regulations on productivity for French manufacturing firms. In particular, we contribute to the literature in three aspects. First, we not only measure economic performance using total factor productivity (TFP), but also incorporate operating margin to investigate the financial performance of French firms. Secondly, we examine the similarities and differences between pollution intensive and non-pollution intensive firms in the French context. Finally, Kozluk and Zipperer (2015) suggest that most of the existing empirical studies use country level or sector level data. Unlike more aggregated data, our firm-level data allows us to identify the level of investment in eco-innovation which is less sensitive to macroeconomic shocks that may be correlated with country or sector level eco-innovation and environmental regulations.

To briefly summarize our findings, we find that at the current stage, stricter environmental regulations harm firms productivity and meanwhile regulation induced eco-innovation is not able to offset this negative effect for French innovators. Furthermore, we find that it is firms that pay higher integrated abatement expenditures that has the main influence on the decline of productivity in France. Meanwhile, we find stringent regulations have no impact on firm's profitability after all, whereas regulation induced eco-innovation significantly reduces firm's profitability and this significant effect indicates the high initial costs for eco-innovation which could potentially harm firms competitiveness. Overall, we do not find sufficient evidence supporting the Porter hypothesis that strict environmental regulations could induce efficiency and stimulate innovation that helps firms improving competitiveness in the market.

The remainder of this chapter is organized as follows: Section 2 illustrates the environmental regulation framework in France and Section 3 provides a brief literature review of both the theoretical and empirical analysis. Section 4 provides a comprehensive description of the data sets and presents our empirical strategy. Section 5 discusses our results. The final section concludes.

2.2 Background

In this section, we provide a detailed introduction to the environmental regulations applied to French manufacturing sectors. French environmental regulatory framework is substantially influenced by EU laws and specifically in the Environmental Code, most of the relevant laws and decrees have been codified. The Environmental Code focuses on three dimensions including resource consumption, climate change, and pollution emission.

Regarding resource consumption, as an important resource, lands are regulated by two land-use regulations, namely solidarity and urban regeneration establishes metropolitan plans (SCoT) and local land use plans (PLU). A construction project needs to comply with local land use plan which gives permission based on several criteria including an environmental impact report. Furthermore, the planning tax is applied to all activities of building that require permission to build based on the surface of the new construction.

The value of planning tax in 2014 was 705 per square meter, and for different municipalities across France, this rate fluctuates between 1% and 5% across different municipalities. Second, water consumption is charged with certain rates which depend on various criteria set by the government. In addition, groundwater is considered more valuable with a higher tax rate than surface water. Third, extended Producer Responsibility (EPR) schemes are specifically introduced in France to increase recycling of materials. For each EPR, manufacturers pay non-profit private companies which recycle wastes. The rate of the payments depends on manufacturers output level. Fourth, fuel consumption is also regulated by the French government and the tax rates vary across different types of fuels. Although collecting government revenue is the primary target for setting up fuel taxes, fuel taxes efficiently restrict fuel consumption and the accompanied emissions. For instance, industries such as chemical, cement, non-metallic products in France exempt from fuel taxes like many other European countries (Baranzini et al., 2000).

Carbon emissions are regulated through two panels: the domestic tax system and the European Union Emission Trading Scheme (EU-ETS). France's carbon tax was first introduced on April 1st 2014 at a rate of 7 per tonne of carbon dioxide (CO2) equivalent (OECD, 2014). However, carbon taxes are included in the Internal Consumption Tax on Energy Products, which applies to firms that produce, import, and/or store fossil fuel. Thus carbon tax is passed on to consumers through higher price. The EU-ETS is a cap-and-trade system for green house gases emissions that covers every EU members. The EU-ETS entered into force in 2005. Until 2016, Emissions from installations in the system has been falling by slightly over 8% compared to the beginning (European Commission, 2016). According to EU-ETS, emissions from firms are not allowed to exceed preset levels which depend on a number of criteria . However, trading emission permits on the market with other firms that receive emission allowances is allowed. Except emission intensive sectors, not all manufacturing sectors are covered by the EU-ETS,.

In France, the government regulates emissions through the tax system "Taxe Generale sur les Activites Polluantes" (TGAP). In 2017, 18 pollutants such as sulfur oxides and other sulfur compounds, hydrochloric acid, etcetera are included, and the tax rates are subject to pollutants. TGAP levies taxes on firms with a polluting activity or selling polluting products: waste, harmful emissions, oils and fossil fuels, detergents and extracted resources (of France, 2019). In addition, firms in waste storage and waste incineration sector have a specific TGAP rate depends on the wastes. Finally, water pollutants including suspended solids, chemical oxygen demand (COD), biochemical oxygen demand (BOD), reduced nitrogen, phosphorus, metals and metalloids, inhibitors, Adsorbable Organic Halogen (AOX), and thermal pollution are charged. A category of stringency is attributed to each watershed components given their level of pollution. There are three categories from lax to strict. The rate of the fee varies across pollutants.

2.3 Literature review

The debate on the economic costs of environmental regulations has been taking place for decades. The conventional point of view suggests that stricter environmental regulations raise costs which weaken firms' competitiveness in the market (Christainsen and Haveman, 1981; Gollop and Roberts, 1983). Environmental regulations impose additional financial constraints on firms' productive activities in two ways. First, firms face direct costs such as end-of-pipe products or process-integrated technologies to adjust production processes. Second, due to financial constraints, firms' budgets are bounded. By devoting additional resources to comply with environmental regulations, there are potential opportunity costs for the firms since they are unable to invest in other profitable opportunities.

In contrast to the conventional point of view, Michael Porter associated environmental regulations with positive performance impacts of affected firms for the first time in 1991 (Porter, 1991). The argument was further elaborated in Porter and Van der Linde (1995) and known as the Porter hypothesis. The hypothesis is as follow: environmental standards can trigger innovation in firms and therefore allow them to offset the costs of complying with these standards. Critical to their argument is that firms would not innovate in the absence of government regulation. The authors propose that regulations can unlock profit opportunities that firms otherwise could not have developed alone by opening up new markets. In addition, regulations can also reduce uncertainty about future demands for new technologies and hence lead to a higher level of R&D investment than without regulation.

More specifically, Porter and Van der Linde (1995) suggest that environmental regulations may affect firms' productivity in two ways. First, the direct effect of regulations on productivity implies that firms are forced to re-evaluate their production procedures to meet regulatory requirements. And this involuntary action comes with extra capital costs as regulation abatement expenditures, thus regulations tend to lower firms' productivity. Second, environmental regulations may affect firms' productivity through innovation. Environmental regulations cause firms to invest more resources to innovation and some of these innovations could reduce negative environmental externality. Nevertheless these triggered innovations may offset the additional costs and even enhance productivity. Furthermore, Porter and Van der Linde (1995) suggest the impact of environmental regulations on productivity may not be significant in the short run since innovation is not necessarily a short term process. It can take a relatively long time to invent a technology in response to an existing environmental regulation and that may affect current profit. However, eco-innovation would provide an early mover advantage.

Jaffe and Palmer (1997) extend the Porter hypothesis by introducing three distinct variants of the Porter hypothesis, namely "weak," "narrow," and "strong" version. The "weak" version argues that well designed environmental regulations may stimulate innovation and this argument does not indicate the types of innovation. The "narrow" version suggests that flexible environmental regulations give firms greater incentive to innovate than prescriptive forms of regulations. Finally, the "strong" version posits that well designed environmental regulations may induce innovation which would compensate for the cost of compliance, thus environmental regulations could potentially enhance firms' competitiveness.

A number of studies examine the impact of strict environmental regulations on economic performance and empirical evidence is considerably mixed (Ambec et al., 2013; Kozluk and Zipperer, 2015). Early industry-level studies, which tend to find a negative effect of environmental regulations on productivity growth, suffer from problems of identification. Gray (1987) takes both environmental and workers' health and safety regulations into account and tests their effects on productivity growth in U.S manufacturing industries and the author finds that the industries' annual costs associated with pollution control significantly reduce the annual productivity growth rate. Likewise in the U.S context, Alpay et al. (2002) investigate the strong Porter hypothesis for the U.S and Mexican food processing industries. The authors calculate productivity using a micro profit function approach and find relatively mixed results. Their results show an insignificant effect of pollution abatement expenditures on either profitability or productivity growth in the U.S. However, Mexican environmental regulations have a substantial impact on both profitability and productivity growth. While regulatory enforcement reduced profitability significantly, a positive effect on productivity growth is noted. Therefore the authors suggest environmental regulations do not always harm productivity and they improve long run competitiveness to some extent.

Focusing on Quebec manufacturing sectors, Lanoie et al. (2008) provide more evidence for the strong Porter hypothesis. Firstly, the authors measure regulation stringency using the ratio of the investment in pollution-control equipment to the total cost and emphasize the dynamic feature of the Porter hypothesis. According to Lanoie et al. (2008), an environmental regulation implemented at a certain time would influence firm's performance in the next one year or longer period until innovations targeting on coping with this regulation are accomplished. So instead of investigating contemporaneous impact of a regulation, the authors control for this dynamic effect by comparing the effect of environmental regulations on productivity in a certain year and the same effect a few years later when new innovations have been induced. Their results suggest that allowing the dynamic effect, environmental regulations show a negative contemporaneous effect on productivity, however, after a few years, they become less detrimental and even positive.

However, few industry-level studies have examined the whole causality chain, from regulations to competitiveness, through innovation. In the Japan context, Hamamoto (2006) finds a significant and positive effect of pollution abatement expenditures on the R&D expenditures in five Japanese manufacturing sectors over 20 years, thus the author confirms that the strict environmental regulations would stimulate innovation. Further results indicate that the increases in R&D expenditures associated with strict regulations lead to an increase in the TFP growth rate. Likewise, Yang et al. (2012) investigate causal links between pollution abatement expenditures, innovation and productivity in Taiwan. The authors find that the pollution abatement expenditures promote R&D activities, and the induced R&D expenditures stimulated by environmental regulations have a significant positive effect on the growth rate of TFP. More recently, using abatement costs to measure regulation stringency, Rubashkina et al. (2015) find that industry productivity is not significantly affected by abatement costs whereas patenting activities increase in a panel of 17 European manufacturing sectors. However, Franco and Marin (2017) find that downstream stringency affects innovation activities and productivity the most while within-sector regulations only affect productivity but not innovation. The authors confirm the direct effect of regulations on productivity, while the part of the effect mediated by induced innovations is relevant only for what concerns downstream regulations.

Evidence from firm or plant-level studies also shows an inconclusive effect of environmental regulations on productivity growth (Cohen and Tubb, 2018). Gray and Shadbegian (1995) investigate the relationship between regulation stringency and plant-level productivity for U.S paper, oil and steel industries. Their results show that pollution abatement expenditures caused a decline in plant-level productivity in 1980s. Likewise, Jaffe et al. (1995) remark the negative effect of environmental regulations on productivity and suggest that for firms in heavily regulated industries, abatement costs take a relatively small share of production costs, thus environmental regulations should not be expected to be a key determinant of overall competitiveness. Berman and Bui (2001) focus on oil refinery industry which is a heavily regulated sector in the U.S. The authors apply a difference in difference (DiD) approach by comparing the productivity of refineries which are subject to more stringent regulations in the South Coast Air Basin with refineries in other areas. Their results suggest that treated refineries have a higher productivity even though they are subjected to more stringent air pollution regulations. Thus the economic cost of environmental regulations may be overemphasized. However the authors fail to consider plant specific characteristics in their analysis.

Additionally, applying a large U.S panel data with 1.2 million plants between 1972 and 1993, Greenstone et al. (2012) examine the economic costs of air quality regulations using non-attainment designation as a measure of regulation. Their results suggest that stricter air quality regulations reduce TFP by roughly 2.6%. Almost all of the effects occur in the first year of non-attainment status, indicating pollution abatement expenditures reduce productivity in a short term. Gray and Shadbegian (1998) investigate paper mills' technology choices in the U.S and find a significant effect of more stringent water and air regulations on investment choices of paper mills. Such regulations encourage new mills to invest more in eco-innovation. Nevertheless, mills which have relatively higher pollution abatement expenditures tend to invest less in productive capital, and these losses have larger magnitudes comparing with the increased abatement investments, leading to lower total investments in high pollution paper mills. Though, their findings imply that stricter regulations tend to reduce investments and relocate investments from production to abatement, which is against the strong Porter hypothesis. Testing for all variants of the Porter hypothesis, Lanoie et al. (2011) suggest that environmental regulations shift firm's R&D direction by which invest more in R&D activities specifically targeting on environmental protection. Their results confirm the weak Porter hypothesis that environmental regulation stimulates innovation, furthermore, the induced eco-innovation has a positive effect on firm performance. However, the magnitude of the negative effect of environmental regulations on firm performance is greater than the indirect causal link mediated with R&D expenditures. Therefore, strong Porter hypothesis is not supported.

Rennings and Rammer (2011) examine the effect of regulation-driven eco-innovation on innovation performance and profitability using 2003 Germany MIP survey and in general, the authors find insignificant effects of environmental regulations on innovation activities and profitability. However, when differentiating between product and process eco-innovation, Rennings and Rammer (2011) show that the process eco-innovation triggered by environmental regulations significantly reduce profit margin. Nevertheless, the limitation of cross-sectional data restricts a generalization of the results. Rexhäuser and Rammer (2014) measure profitability by return on sales (ROS) and identify two types of innovation activities, type one improves firm's material and energy efficiency, and the other type does not. The authors estimate the relationship between innovation activities and firm profitability in Germany and they only find partial evidence supporting the strong Porter hypothesis. These results suggest that only eco-innovation which improves resource efficiency positively improves profitability. However the use of ROS may lead to potentially biased results since accounting-based information also includes non-operating incomes. Nevertheless, the measurement on eco-innovation is debatable since this study mainly considers eco-innovation adopted without taking other technological capabilities into consideration. A recent study from Van Leeuwen and Mohnen (2017) examine the impact of regulation stringency on productivity through eco-innovation for Dutch manufacturing firms. Similarly, this study does not show an overall significant effect of eco-innovation on productivity. The authors further distinguish between product eco-innovation and process eco-innovation, and suggest that process eco-innovation significantly increases TFP whereas product eco-innovation tends to reduce TFP.

2.4 Data and empirical strategy

2.4.1 Data

To investigate the causal links among environmental regulations, eco-innovation and firm performance, we merge four data sets to construct an unbalance panel data for French manufacturing firms. First, ANTIPOL survey (Survey on environmental protection studies and investments) is included in order to obtain information on regulation stringency at the firm level. Secondly, financial information on manufacturing firms is obtained from two data sets, namely the Unified and Comprehensive File of SUSE (FICUS) database and the Approached File of ESANE Results (FARE). Finally, we include the Annual Survey on the Resources Devoted to R&D Activities (Enquete annuelle sur les moyens consacres a la R&D) collected by the French Ministry of Education and Research in our panel. Detailed explanation regarding four data sets has been discussed in Chapter 1.

After merging four data sets presented above, we remove inconsistent observations and errors from our sample, such as incomplete data, negative values for investment and other contradictory information between different data sets. In addition, we drop all firms with less than 10 full-time equivalence employees. All monetary variables are represented in the unit of thousand Euros and have been deflated using French Producer Price Index at the sector level with 2010 as a baseline (INSEE, 2017). Our final unbalanced panel data comprises almost 4,800 observations for about 1,500 French manufacturing firms during 2004-2011. We also distinguish between pollution intensive sectors and non-pollution intensive sectors. In line with Shimamoto (2017), we categorize the five pollution intensive sectors including Manufacture of pulp, paper and paper products, Manufacture of chemicals, chemical products and man-made fibres, Manufacture of coke, refined petroleum products and nuclear fuel, Manufacture of other non-metallic mineral products and Manufacture of basic metals and fabricated metal products.

2.4.2 Empirical strategy

2.4.2.1 Environmental regulations and performances

We investigate the overall effect of regulation stringency on productivity. Environmental regulations may affect productivity through several channels. First, the firm would devote additional inputs to comply with environmental requirements which we refer to as the direct effect. Thus, higher production costs may reduce productivity. On the other hand, environmental regulations could trigger innovation which may increase productivity, we refer to this as the indirect effect. To investigate the mechanism behind these effects, this study applies a two-step approach following Hamamoto (2006) and Lanoie et al. (2011). In the first step, we examine the determinants of environmental R&D with respect to environmental regulations. Following previous studies (Kesidou and Demirel, 2012), the first step of the model is specified as follow:

$$Log\_EnvR\&D_{i,t-1} = \beta_1(TFP_{i,t-2}) + \beta_2(F_{i,t-2}) + \beta_2(T_{i,t-2}) + \beta_3(P_{i,t-2}) + \mu_i + \gamma_t + \epsilon_{i,t} \quad (2.1)$$

where Log_EnvR&D is the log of environmental R&D expenditure of firm i in year $t-1$. Table 2.1 defines our variables. In the first set of variables F, we include firm specific factors (Del Río et al., 2017) including firm age, firm size, average wage, ownership of firm, market share and leverage. Then in the second set of variables T, we include a series of variables to capture firms' technological capabilities and includes R&D intensity, external cooperation R&D dummy, public funding dummy, EMS dummy and EMS_process dummy. Finally, we include abatement intensity as our policy instrument in the set of variables P. In addition, we take into account time-invariant characteristics through random effect μ and fix parameters of regional, time and sector dummies, namely γ_t. Regional and sector dummies are included to control for time invariant factors common to firms across different regions and sectors respectively and meanwhile we include year dummies to account for business cycle effects. Given the potential reverse causality if firm environmental R&D causes changes in firm productivity, we impose a lag structure to control for the delayed effect and to resolve the reverse causality concerns. The estimation results for 2.1 is presented in 2.2.

[Table 2.1 about here]

[Table 2.2 about here]

Based on the estimated environmental R&D expenditure in the first stage, we further examine the impact of induced environmental R&D on productivity. As TFP denotes the contribution to value-added excluding labor and capital in the production function, it is generally specified as a function of firms' technological activity measure and other factors in the productivity literature. Thus after estimating the regulation induced eco-innovation from Equation (1), the second step of the model is specified as follow:

$$TFP_{i,t} = \beta_1(fitted\_Log\_EnvR\&D_{i,t-1}) + \beta_2(F_{i,t-1}) + \beta_3(T_{i,t-1}) + \beta_4(P_{i,t-1}) + \mu_i + \gamma_t + \lambda_{i,t} \tag{2.2}$$

where TFP is the total factor productivity of the firm i at year t. To elaborate our argument on firm performance comprehensively, we use the estimated environmental R&D expenditure from Equation 2.1 to estimate the effect of induced environmental R&D expenditure on firm profitability, the model is specified as follow:

$$\begin{aligned} Operating\_margin_{i,t} = {} & \beta_1(fitted\_Log\_EnvR\&D_{i,t-1}) + TFP_{i,t-1} + \beta_2(F_{i,t-1}) + \beta_3(T_{i,t-1}) + \\ & \beta_4(P_{i,t-1}) + \mu_i + \gamma_t + \lambda_{i,t} \end{aligned} \tag{2.3}$$

where Operating_margin is the operating profit margin of firm i in year t.

2.4.2.2 Dependent variables

In this chapter, we empirically test whether stricter environmental regulations are associated with better economic performance. Economic performance is explained with two dimensions, namely productivity and profitability. Firstly, productivity is measured by TFP which is the portion of output not explained by the amount of inputs used during production. TFP reflects the efficiency of firms and how effective inputs are being used in utilizing production (Greenstone et al., 2012). Regarding TFP, we denote logs and levels using lower case letters and upper case letters respectively. We assume that firms produce a homogeneous good following a Cobb-Douglas production function:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + e_{it} \tag{2.4}$$

where y_{it} is the log of value added of firm i at time t, k_{it} is the log of capital, l_{it} is the log of labour, e_{it} is an error term and ω_{it} is the firm's productivity. It's assumed that capital evolves following a certain law of motion that it is not directly related to current productivity shocks, whilst labour is an input which can be adjusted whenever the firm responses to a productivity shock. The OLS estimators would be bias due to the correlation between labour input and productivity (Ackerberg et al., 2015).

Due to the endogeneity problem of traditional solutions explained above, Levinsohn and Petrin (2003) (LP) propose an two-step approach which use intermediate inputs (investment denoted i and materials denoted m) to proxy for the unobserved productivity. This approach firstly assumes monotonicity holds between intermediate input's demand function and ω to obtain $\omega_{it} = \omega(k_{it}, i_{it})$. Thus, Levinsohn and Petrin (2003) re-write Equation 2.4 as:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + e_{it} + \omega(k_{it}, i_{it}) = \beta_l l_{it} + \phi(k_{it}, i_{it}) + e_{it} \tag{2.5}$$

Secondly, assuming productivity evolves following an exogenous first-order Markov process: $\omega_{it} = E[(\omega_{it}|\omega_{it-1})] + \xi_{it}$ where ξ_{it} is a random shock which is uncorrelated with k, Equation for the second stage changes to:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \xi_{it} + E[(\omega_{it}|\omega_{it-1})] \tag{2.6}$$

However, the above two step procedure approach suffers from functional dependence problems that the moment condition underlying the first stage estimating equation does not identify the labor coefficient. More specifically, Ackerberg et al. (2015) argue that labour is a deterministic function of the set of variables that, in the LP procedures, needs to be non-parametrically conditioned on. Hence, under this non-parametric condition, there is no variation in labor left to identify the labor coefficient. Instead of using two-step estimation, Wooldridge (2009) combines the moment conditions of both stages into a single set and obtains efficient GMM estimates and standard errors in one step. In particular, Wooldridge (2009) suggests using polynomials of order three or less to approximate $\phi(k_{it}, i_{it}$ and $E[(\omega_{it}|\omega_{it-1})]$ in order to estimate firm's productivity.

In this study, we apply a version of the Wooldridge (2009) method extended by Doraszelski and Jaumandreu (2013) which account for R&D investment in determining the difference in firm-level productivity across firms over time. Doraszelski and Jaumandreu (2013) approach is based on an assumption that the impact of R&D investment on productivity occurs through the function $E[(\omega_{it}|\omega_{it-1})]$. This assumption implies $\omega_{it} = E[(\omega_{it}|\omega_{it-1}, r_{it-1})] + \xi_{it}$ where r_{it-1} denote the lagged log of R&D expenditure. This assumption allows for considering the link between R&D and productivity endogenously without explicitly modeling how the knowledge capital accumulates.

Secondly, as another crucial criteria in measuring firm performance, profitability also affects firm growth and the ability to compete in the market. We measure firms' profitability in terms of operating margin which is defined as the ratio between operating profit and turnover. Previous studies by Ghisetti and Rennings (2014) and Rassier and Earnhart (2015) use return on sales (ROSs) to proxy for profitability. Their measurement has a potential flaw since the way to calculate ROSs is to divide pre-tax profits over total sales. Pre-tax profits are inclusive of environmental taxes, thus ROSs are potentially correlated with environmental stringency which leads to inconsistent estimates. By using absolute profits after tax to generate operating margins, we are able to overcome the potential endogeneity concern. Furthermore, we apply a lag structure and due to the time span of our panel data is relatively short, we only lag all explanatory variables one year. This lag structure allows overcoming endogeneity problems deriving from the simultaneity between dependent variable and explanatory variables and the potential reverse causality issue. Productive firms could be more profitable, however, a firm's profitability not only depends on its own productivity level but also on the productivity level of the other rivals. We control for this concern by using Herfindahl-Hirschman Index (HHI) which is a widely used proxy for product market competition (Valta, 2012).

2.4.2.3 Explanatory variables

The measurement of environmental regulation stringency is an essential issue in the field of environmental economics. A number of different measurements for regulation stringency have been adopted in existing empirical studies. A large stream of studies specifically investigate the effect of one particular regulation which is more precise in capturing causal links, but at the cost of the generality of conclusions. The proxies used range from pollution abatement expenditures (Greenstone et al., 2012), survey-based policy perceptions (Lanoie et al., 2011). Regarding regulatory instrument, in our econometric analysis, we introduce environmental abatement intensity as our proxy for environmental stringency.

In ANTIPOL data, the abatement costs focus on two dimensions: "investments" (hardware entirely dedicated to environmental protection, purchases of production facilities more efficient in terms of environmental issues) and "studies" (regulatory or investment-related). First, investments are defined as "the purchases of buildings, land, machines or equipment intended to treat, measure, control or limit the pollution generated during production". These investments can be either the purchase of specific equipment entirely dedicated to environmental protection regarding seven different pollutant categories (such as skips, filters, retention tanks, pollution measuring instruments) or the purchase of more efficient process changing equipment in environmental matters regarding seven pollutant categories (such as acquisition of less polluting electric vehicles, machines emitting less, generating less waste, consuming less water or less noisy). Second, studies are defined as "the purchases of services or internal costs intended to improve knowledge or to establish a summary of the effect of production activities on the environment (excluding expenses intended for the development of eco-products)". For instant, studies includes all regulatory studies such as danger studies, natural risks reports, reports investigating the impact of production activities on the environment, as well as audit files (files of preparation for ISO 14001 certification or EMAS) and ICPE files (Classified Installations for the Protection of the Environment).[2] We consider "investments" as end-of-pipe investments and sum up these investments across different pollutant categories. Likewise we generate integrated investments using "studies". Furthermore, we sum up total integrated and end-of-pipe investments to construct the total abatement costs. This variable includes expenditures due to the operation of abatement capital, expenditures due to environmental taxes and expenditures due to environmental management such as the training of managers or the purchase of services. These expenditures exclude expenditure for labour health and security and expenditure that allows a reduction of material or energy use. Thus the abatement intensity is calculated by dividing total abatement costs by total sales.

We measure eco-innovation using the firm-level environmental R&D expenditures. Among

[2] These expenditures exclude expenditure for labour health and security and expenditure that allows a reduction of material or energy use.

existing firm-level studies, majority of them are based on subjective measures of the motivation to undertake eco-innovation from different survey data sets (Del Río et al., 2011; De Marchi, 2012; Del Río et al., 2017; Jové Llopis et al., 2017). Unlike previous studies, in our R&D survey, firms are specifically asked for the distribution of internal R&D and one of the categories is the percentage of R&D expenditure dedicated to environment protection. Our environmental R&D expenditure variable is therefore calculated by multiplying the share of environmental R&D expenditures with the level of total internal R&D expenditures. This variable captures the extent of a firm's internal R&D investment in environmental innovation, and is more precise than the majority of R&D based eco-innovation indicators employed in the literature. Surveys investigating environmental R&D activities often ask firms whether they conduct environmental R&D but do not specifically ask about environmental R&D intensity (Horbach, 2008). Some earlier studies utilize total R&D expenditure as an indicator for eco-innovation (Jaffe and Palmer, 1997; Brunnermeier and Cohen, 2003) based on the assumption that there is a strong correlation between eco-innovation and general innovation. This is potentially problematic as eco-innovation could crowd out general innovation. Thus, one of the advantages of our variable is that it focuses specifically on R&D expenditures allocated to environmental protection instead of all types of R&D expenditures.

We use information on the cooperation on R&D with external partners. The dummy variable "ExtRD_d" indicates if the firm was subcontracting and collaborating on R&D with external firms or institutions. Following De Marchi (2012), the variable "R&D_intensity"

expresses R&D intensity as the ratio between the number of R&D activities related employees and the total number of employees. Furthermore, we use public funding as an indicator of innovation related public policies. The variable "Pubfunding_d" equals to one if a firm received funding for R&D activities from public resources.

We capture information about the organizational capability of a firm by measuring a firm's engagement with environmental management systems. In line with Costa-Campi et al. (2017), ISO 14001 approval is one of the most widely used measures of environmental management systems together with the Eco Management and Audit Scheme (EMAS). ISO 14001 can be used by any firm, regardless of its activity, and aims to set up an environmental management system and obtain a certification for their productive process. ISO 14001 has been frequently included as a determinant of eco-innovation and has been found to be effective in stimulating environmental R&D (Kesidou and Demirel, 2012). Meanwhile, environmental management system has a strong link to the improved perceived future financial performance (Klassen and McLaughlin, 1996). ISO 14001 accreditation is obtained from the ANTIPOL data set and has been available since 2002. Furthermore, with regard to organizational capability, the ANTIPOL data set provides two more variables "SME" and "EMS_process". "SME" is a binary variable which equals one if a firm holds other environmental management systems other than ISO 14001. "EMS_process" is a binary variable which equals one if a firm is in the process of obtaining environmental certificate. Due to the fact that "ISO" and "SME" variables only partially capture the effect of environmental management system, we construct a new variable namely EMS which equal to one if either of the above two variables is equal to one. Since all these variables are at plant-level and it is possible that only one plant among several plants for a firm has environmental managements systems. We assume that if a plant of a firm is accredited environmental management systems, then this firm is also accredited with having an environmental management system.

Market structure is an important factor that affects firm's productivity as well as profitability (Syverson, 2004; Rexhäuser and Rammer, 2014). Productive firms could be more profitable, however, a firm's profitability not only depends on its own productivity level but also on the productivity level of the other rivals. Market concentration is a substantial indicator of market structure that highly concentrated market poses different competitive conditions on firms and high competition forced firms to improve their productivity to stay in the market. The intensity of the competition within an industry depends on intra market concentration, hence firms in a highly concentrated industry have low incentive to raise their productivity (Syverson, 2011). Nevertheless, as Rexhäuser and Rammer (2014) suggest,a firm's market share represents the efficiency level of the firm, thus a high market share indicates advanced productivity and profitability in the past. We measure market concentration using a normalized HHI at the two digit level of NACE rev.1 classification. Obtaining data on total output from FICUS and FARE data set, we firstly calculate the market share of each firm and further divided by total industry output to construct this index.

The export variable takes into account the influence of trade on productivity and profitability. This variable is included since exporters generally have higher productivity through R&D and are characterized as having higher innovation propensity(Añón Higón et al., 2011). To the extent that foreign markets are competitive and product variety is valued, we expect exporters to be more competitive. In particular, if a significant number of foreign markets demand green products, then the opportunity to improve company performance or charge premium prices via exports could make eco-innovation more profitable. Thus, we would expect positive effects of export on firm performance indicators. To control for the effect of financial constraints on firm productivity and profitability, we measure leverage by calculating the debt-to-equity ratio. In line with Lee and Min (2015), we calculate the debt-to-equity-ratio as Debt divided by (Debt plus Equity).

We include a series of standard control variables. First, unit costs of production and further profitability may be affected by the scale of production. Large firms could be more efficient in production due to more specialized inputs, better coordinated resources. However small firms could be more efficient since they have flexible, non-hierarchical structures, and do not usually suffer from the so-called agency problem (Halkos and Tzeremes, 2007). We capture scale effects by including firm size in our analysis. The corresponding variable "Log_size" is the log of the number of full-time equivalent employees. Firm age is included as an indicator for accumulated organizational resources and is expected to positively related to productivity because of learning by doing. Although younger firms may also be more productive as a mechanism to increase market share. Hence, the variable "Log_age" is measured as the log of age in years generated by deducting firms' creation year from the current year. We control for the input price by including a control variable "Log_avewage" which is a proxy for the price of labour. We measure this by the ratio between salaries paid to the employees and firm total number of employees.

In addition, we take into account invariant characteristics through using time dummies and two digit NACE sector dummies to control for business cycle effects common to all business. Furthermore, we control for the regional differences by introducing regional dummy variables which cover 25 administrative regions.[3]

The sample we use in our econometric analysis comprises 1,524 French manufacturing firms and 4,851 observations between 2004 and 2011. Of the 1,524 firms, 754 firms do some environmental R&D investment, which represent 34.09% of the firms in our sample. Table 2.3 presents the summary statistics for our independent variables. The average size of the firm is approximately 665 full-time equivalent employees thus our sample consists of relatively large firms. Likewise the average export dummy is around 95% which shows that a large majority of firms in our sample are exporters which is again a result of our sample being restricted to large firms.

[Table 2.3 about here]

[3] 25 administrative regions comprise 22 regions in Metropolitan France and 3 overseas regions. Since in 2014, the French parliament passed a law reducing the number of metropolitan regions from 22 to 13 effective 1 January 2016, we adopt the previous legal concept of regions.

Figure 2.1 plots average investment in eco-innovation over time, indexed so that 2004=100. It can be seen that over the period 2004-2011, the average eco-innovation increased by about 150%. This figure reflects the fact that France has been increasingly investing in eco-innovation in recent years. According to the 2015 Eco-Innovation Scoreboard, France ranks seventh among in EU in terms of eco-innovation (Eco-innovation Observatory, 2018). Furthermore in Figure 2.2, we present average investment in eco-innovation over time, again indexed so that 2004=100, distinguishing between pollution intensive and non-pollution intensive firms. The figure shows that although the overall increase in the investment in eco-innovation of 50% for pollution intensive firms over the period, the average investment in eco-innovation has been declining since 2009. Meanwhile, non-pollution intensive firms are investing more resources in eco-innovation.

[Figure 2.1 about here]

[Figure 2.2 about here]

Regarding regulation stringency, Figure 2.3 perform the annual average abatement expenditures for the period of 2004-2011 and we decompose total abatement expenditures into end-of-pipe abatement and integrated abatement. Over this period, we see a steady decreasing trend for over all abatement expenditure whereas integrated abatement expenditures take a relatively small proportion in total abatement expenditures.

[Figure 2.3 about here]

2.5 Empirical results

In Table 2.4, we present our baseline results estimating the influence of environmental regulations on firm productivity (as Equation(2)). All specifications include full set of year, sector and regional dummies (not reported). The first model specification uses total abatement intensity as the indicator for regulation stringency to take into account the direct effect of environmental regulations on productivity, whereas the second specification divides total abatement intensity into two parts: namely integrated abatement intensity and end-of-pipe abatement intensity. Specification (3) excludes the direct effect of abatement expenditure from the estimation. The Kleibergen-Paap F statistics indicates that instrumental variables are strong across all specifications.

In Specification (1), the coefficient of one lag of total abatement intensity is negative and significant at the 5% statistical level which indicates the direct effect of pollution abatement investment significantly reduce firms' productivity. Meanwhile, controlling for the time, sector and regional specific effects, the coefficient of induced environmental R&D is negative but insignificant at the 10% statistical level implying that regulation induced environmental R&D does not indeed contribute to productivity in French manufacturing firms. This finding suggests that more stringent environmental regulations harm firms' competitiveness in terms of productivity directly and the indirect benefit through induced eco-innovation is not observed. Thus, we do not find evidence that eco-innovation offsets the costs of complying with environmental policies. This may be explained as that a large part of the investments necessary to comply with regulations represent additional production costs. Although some of these costs may be offset by the efficiency gains identified through investment in environmental R&D, the net effect is negative.

In Specification (2), we decompose abatement expenditures into two different types of abatement expenditures, namely end-of-pipe (hardware) abatement and integrated (regulatory) abatement. We find that end-of-pipe abatement investment has a negative and insignificant effect on productivity whereas integrated abatement investment has a negative but significant effect on firm productivity. The results suggest that a firm's level of investment in purchasing hardware entirely dedicated to environmental protection or production facilities more efficient in terms of environmental issues in the previous year has no impact on the firm's current productivity, however integrated abatement expenditure would reduce firm productivity. Meanwhile policy induced environmental R&D remains negative and insignificant. Furthermore, when we exclude the direct effect of regulatory stringency on productivity in Specification (3), we still observe a negative and insignificant effect of policy induced environmental R&D on productivity. Thus we do not find evidence to support that eco-innovation promotes productivity after all.

Among the control variables, we find that R&D intensity does not significantly affect productivity. This finding is expected due to the fact that all of our observations are innovators, this could potentially weaken the impact of R&D activities on productivity. However co-operating with external partners in R&D activities has a positive and significant effect on productivity which is consistent with previous study by Yang et al. (2012), supporting the view that external technology cooperation serves as a crucial role in building up firm technological capability which further enhance firms' productivity. The coefficient for "EMS" shows a negative and insignificant effect on productivity, thus holding environmental management system certificate in the previous period has no impact on firm current productivity. However, if a firm is in the process of applying for EMS certificate, a positive and significant effect on productivity is observed. This result may suggest that EMS only enhance productivity in the short run during the application period. Furthermore, market concentration is found to have a positive and significant effect on productivity.

[Table 2.4 about here]

In Table 2.5, we report the results distinguishing between two sub-groups, namely pollution intensive firms and non-pollution intensive firms. Regarding key variables, Specification (1) shows fairly consistent results for polluters comparing with the baseline results in Table 2.4 . We find that abatement intensity remains significantly negative for pollution intensive firms which indicates more stringent environmental regulations essentially reduce productivity. However, in Specification (2), it seems that for polluters, neither end-of-pipe abatement nor integrated abatement has significant effect on firm productivity. Moreover, Specification (1) and (2) confirm that induced environmental R&D remain insignificant in enhancing productivity for pollution intensive firms. Nevertheless, the impact of abatement costs on productivity is slightly bigger for polluters comparing to our baseline model that 1% increase in abatement intensity would decrease TFP by 4.01% on average for polluters. Thus the presence of high abatement costs makes polluters more sensitive to the change in environmental policy. Overall, our results suggest that undertaking eco-innovation can not offset the high abatement pressure for pollution intensive firms. However, lagged R&D intensity has positive and significant impact on the productivity of pollution intensive firms, whilst the R&D cooperation with external partners has no significant effect on productivity for polluters.

In Specification (3), we find that clean sector results show different characteristics comparing with polluters. The results show that lagged abatement intensity does not affect firm productivity significantly in clean sectors. Also comparing with polluters, the coefficient of abatement intensity is relatively small. However the average abatement intensity for firms in clean sectors is almost one third smaller comparing with polluters. Hence, our results suggest that clean firms' productivity is less sensitive to environmental regulations since they are not heavily regulated. Likewise, Specification (3) confirms that induced environmental R&D remains insignificant in enhancing productivity for clean firms.

Since the implementation of changes in the direction of R&D towards eco-innovation takes time, and with the pressure to improve economic performance, firms in pollution intensive sectors have less incentive for undertaking environmental R&D to offset the high abatement costs. Referring to the pollution haven hypothesis, Gray and Shadbegian (1998) suggest that more stringent regulations tend to divert investment from productivity to abatement. Firms in pollution intensive sectors would rather pay off the abatement costs than initiating high cost new eco-innovations.

[Table 2.5 about here]

Estimation results of Equation 2.3 focusing on profitability are presented in Table 2.6. Again, all models include full set of year, sectoral and regional dummies (not reported). The first specification uses total abatement intensity as the indicator for regulation stringency to take into account the direct effect of environmental regulations on profitability, whereas the second specification excludes the effect of TFP from the estimation. Specification (2) decomposes total abatement intensity into two parts: namely integrated abatement intensity and end-of-pipe abatement intensity and furthermore, Specification (3) also excludes the direct effect of regulatory stringency from the estimation. The Kleibergen-Paap F statistics indicates that instrumental variables are strong across all specifications.

From Specification (1), abatement intensity is found to be insignificantly affecting firms' profitability whereas we find a negative and significant coefficient for induced environmental R&D which suggests that in general the adoption of policy induced eco-innovation significantly reduces firms' operating margin. The results do not find evidence to support Porter's hypothesis that regulation improves firm profitability by stimulating innovation that over compensates regulatory costs. When we decompose abatement cost into end-of-pipe abatement intensity and integrated abatement intensity in specification (2), results suggest neither of these types of two abatement intensity has effect on firm profitability. Meanwhile lagged TFP shows that more productive firms are more profitable. When we exclude abatement intensity from our estimation in Specification (3), we find similar results. In general, inventing a new technology is a costly process for the firm and our results indicate that when the new technology is eco-innovation, the costs actually overweight the benefits in a way that the profitability return of such innovation investment becomes negative.

Regarding control variables, we find a positive but insignificant effect of EMS on operating margin which indicates holding environmental management system certificates in the previous period does not affect a firm's current profitability. However, if a firm was applying for EMS in the previous period, its profitability is significantly enhanced. A positive and significant effect of firm age on operating margin is observed, and it suggests that more mature firms are more profitable due to the dynamic economies of scale by learning from experience. More mature firms may also benefit from reputation effects, which allow them to earn a higher margin on sales (Glancey, 1998).
[Table 2.6 about here]

In Table 2.7, we report the results for pollution intensive firms and non-pollution intensive firms. Regarding eco-innovation, Specification (1) shows a contrary result comparing with baseline estimation in Table 2.6 that eco-innovation does not significantly reduce polluters' profitability. However, for non-pollution intensive firms in Specification (3), we find fairly consistent results in comparison with baseline estimation. We observe a significant and negative coefficient for induced environmental R&D expenditure which is different from zero at 10% significance level. This result suggests that for firms in clean sectors, devoting more resources to environmental R&D due to stricter regulations significantly reduces their profitability. However, the direct effect of regulatory stringency remains insignificant.

[Table 2.7 about here]

2.6 Robustness checks

To test the sensitivity of our results, we perform a series of robustness checks. The first set of robustness checks test whether the aggregation at the plant-level affects our main results. To address potential aggregation bias from plants to firms, we restrict the sample to a certain group of firms. We include firms in the sample according to the ratio between each firm's total number of full-time equivalent employees for plants from the ANTIPOL and the firm's total number of full-time equivalent employees from the FARE and FICUS data. First, we aggregate the total number of full-time equivalent employees across all plants surveyed in ANTIPOL at the firm level. Second, we use the employment data composed by FARE and FICUS to construct the ratio. A ratio equal to 100% suggests that there is no measurement error due to the aggregation. Firms with this ratio below a certain threshold are excluded from the sample.

We present baseline estimation results of equation (2) and equation (3) using different thresholds in Table 2.8 and Table 2.10 for productivity and profitability respectively. In Table 2.8 for productivity, model (1) reports the estimation on the whole sample which can also be referred as 0% threshold, model (2) reports the threshold of 50%, model (3) reports the most restricted threshold of 75%. Particularly focusing on key variables "Log_EnvR&D" and "Abatement_intensity", results are consistent across different thresholds. However, we notice that magnitudes of the coefficients change when we increase the threshold.

[Table 2.8 about here]

These changes in magnitudes of the coefficients could arise from two possible reasons. First, the measurement bias could be lower when we use a restricted sample which suggest if the measurement bias generate endogeneity, then the estimates for the restricted samples are less biased. Second, the composition of sample changes due to the threshold which suggest only firms belonging to certain sectors appear in the most restricted sample. The selections may be endogenous and generate further bias in estimations. For instance, firms in pollution intensive sectors are those mostly selected in the 75% threshold sample, since even their smallest plants have to answer the ANTIPOL survey whereas plants in clean sectors do not.

With regard to standard deviations, the coefficients for regulatory stringency (Abatement_intensity) are negative and significant across different thresholds and the coefficients for induced eco-innovation (Log_EnvR&D) remain insignificant. These results confirm our assumption that the threshold methodology lower the potential bias raised from aggregation process. Table 2.9 reports the distribution of firms by sectors for the 0% threshold sample and the 75% threshold sample. From Table 2.9, we observe that there is no substantial difference in the composition of the sample between these two groups, so we may reject our second assumption that the effect of sample composition is very small in our case.

[Table 2.9 about here]

Furthermore, we apply the same threshold methodology to test the robustness of our result on profitability in Table 2.10. Similarly, We find consistent result across thresholds. The coefficients for regulatory stringency (Abatement_intensity) are insignificant along with the negative and significant effect of induced eco-innovation (Log_EnvR&D) on a firm profitability across different thresholds. Thus, we conclude that our main results are not highly sensitive to the aggregation procedure from plant level to firm level.

[Table 2.10 about here]

Secondly, to address the endogeneity concerns regarding instruments are correlated with omitted unobserved heterogeneity, we implement a system generalized method of moments (GMM) approach. The System GMM estimator yields efficient and consistent parameter estimates, given that the regressors might not be strictly exogenous (Blundell and Bond, 2000). We include one year lag of the dependent variable as an additional regressor to transform the static model into a dynamic one and we instrument potential endogenous variables with their three periods lagged value. We present system GMM estimation results in Table 2.11 and Table 2.12 for productivity and profitability respectively. Regarding productivity in Table 2.11, the hypothesis of the absence of the second-order serial correlation in disturbances is not rejected in each specification, hence lags of endogenous variables are appropriate instruments in our estimations. The hypothesis of over identification of the instruments is not rejected in each specification either, ensuring the validity of the instruments. First we notice a strong degree of persistence in TFP. Regarding key variables, results for GMM approach are highly consistent with IV results in Table 2.4 that abatement_intensity remains negative and significant whereas eco-innovation show no significant impact on TFP.

[Table 2.11 about here]

In Table 2.12, we pass the tests on the presence of second order serial auto correlation and the Sargan and Hansen tests on over-identification which justify the validity of our estimation. Results are also consistent with IV results in Table 2.6 which suggest that policy induced eco-innovation reduces a firm's profitability significantly whereas the direct effect of abatement costs on profitability is not significant. Overall, we confirm that our results are robust to changes in estimation techniques.

[Table 2.12 about here]

Finally, we compute TFP using different measurements to test whether different TFP estimation techniques alter our results. As discussed in the previous section, we estimate the Levinsohn and Petrin (2003) approach which is a two step approach based on using material and investment respectively to proxy for the firm's unobserved productivity. Also, we estimate the Wooldridge (2009) approach which is a new approach combining the moment conditions into a single set to obtain efficient GMM estimates in one step. The correlation coefficients between these measurements of TFP are relatively high and Table 2.13 shows that the estimated coefficients for our key variables across three different specifications are highly consistent. The results hold for different measurements of TFP which confirm the robustness of our results.

[Table 2.13 about here]

2.7 Conclusions

The Porter hypothesis challenges the traditional view on the economic cost of environmental regulations by suggesting that more stringent environmental regulations may trigger innovation which eventually enhances a firm's productivity and offsets the cost of regulations. Porter's idea of a "win-win" option is the driving force behind policy initiatives.

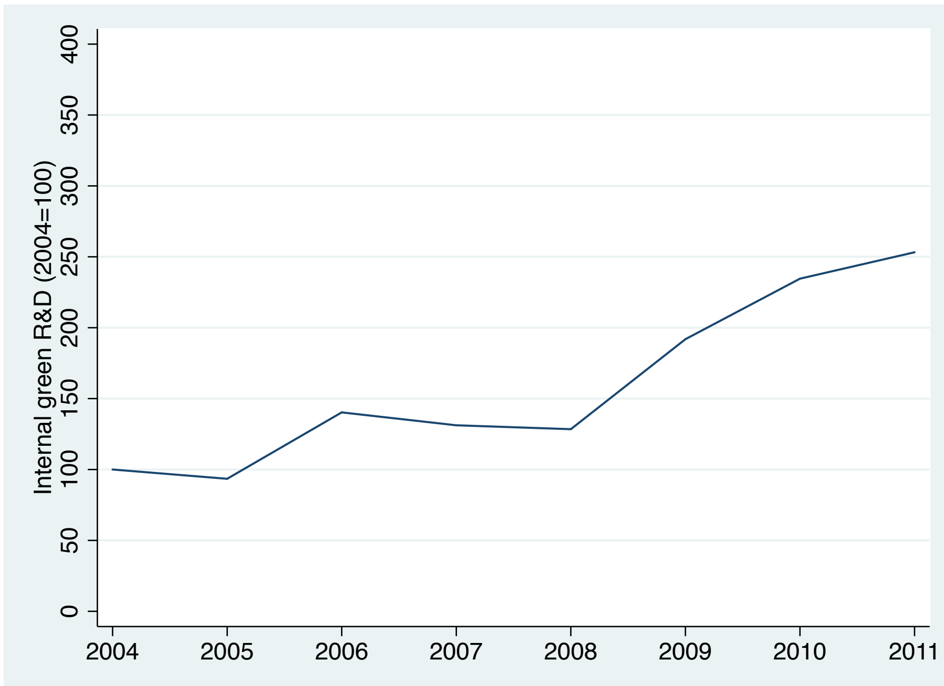
In this chapter we examine the impact of environmental regulations on firm performance measured by productivity and profitability using a firm-level panel data of French manufacturing firms that invest in R&D. To overcome some data limitations of earlier studies, we construct a panel data set containing 1,524 French firms that covers the period 2004-2011 with information obtained from varies of sources concerning innovation, environmental activities and financial information.

More specifically, we measure environmental abatement costs to capture regulatory stringency and investigate whether stringent environmental regulations weaken firms' productivity. In addition we test whether regulatory induced eco-innovation could offset environmental abatement pressure, known as the Porter hypothesis. Finally, we provide new evidence on the relationship between regulatory stringency and profitability. Our unique firm-level sample means that unlike studies that use more aggregated data, we are able to use an identification strategy that is less sensitive to macroeconomics shocks that may be correlated with country or sector level eco-innovation and environmental regulations. Our results show that at the current stage, stricter environmental regulations harm firms' productivity and also eco-innovation is not able to offset this negative effect for French manufacturing firms. Also, we find regulations have no impact on firm profitability after all, whereas regulation induced eco-innovation significantly reduces profitability. Overall, we do not find sufficient evidence to support the strong Porter Hypothesis.

This study has important policy implications. Our findings indicate that stringent regulations harm firm productivity and meanwhile the impact is rather unidentified on firms' profitability. Meanwhile, regulation induced eco-innovation does not seem to lead to a beneficial competitiveness effect. However, evaluation of competitiveness involves multiple dimensions and the negative effect from environmental regulations should not be over-estimated by policymakers. Dechezleprêtre and Sato (2017) suggest that eco-innovation triggered by regulations spillover the whole economy and are beneficial to societies. A multidimensional framework is needed for policymakers to evaluate and modify the current policy mix. Our results give further evidence against the Porter Hypothesis. As environmental policies do not lead to better economic performance, and eco-innovation is not able to mediate this effect of policies on firms economic performance.

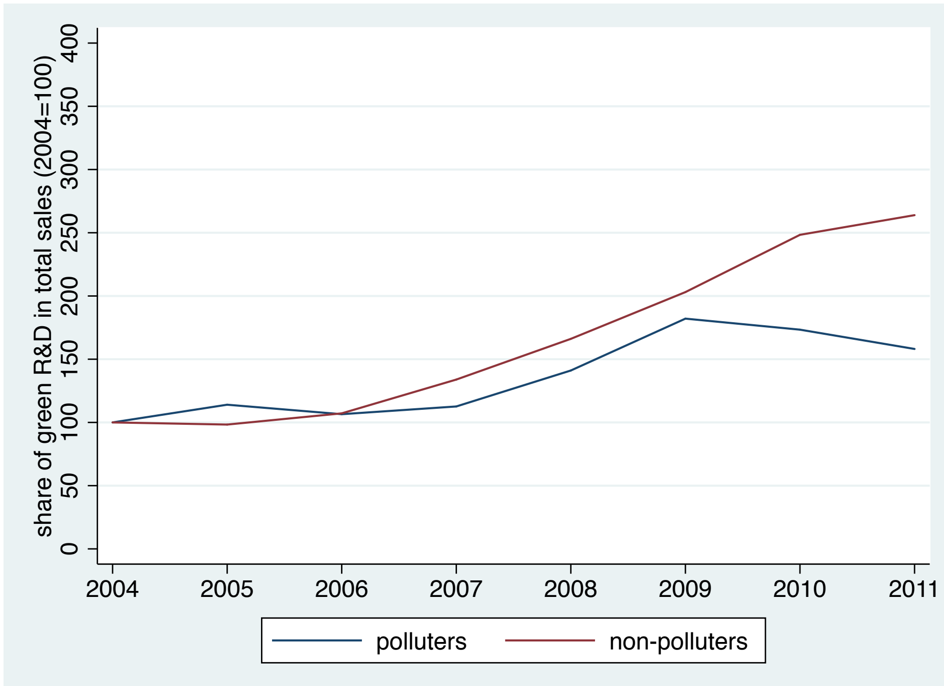
2.8 Figures and tables

Figure 2.1: Trend of average eco-innovation of French manufacturing firms (2004-2011)



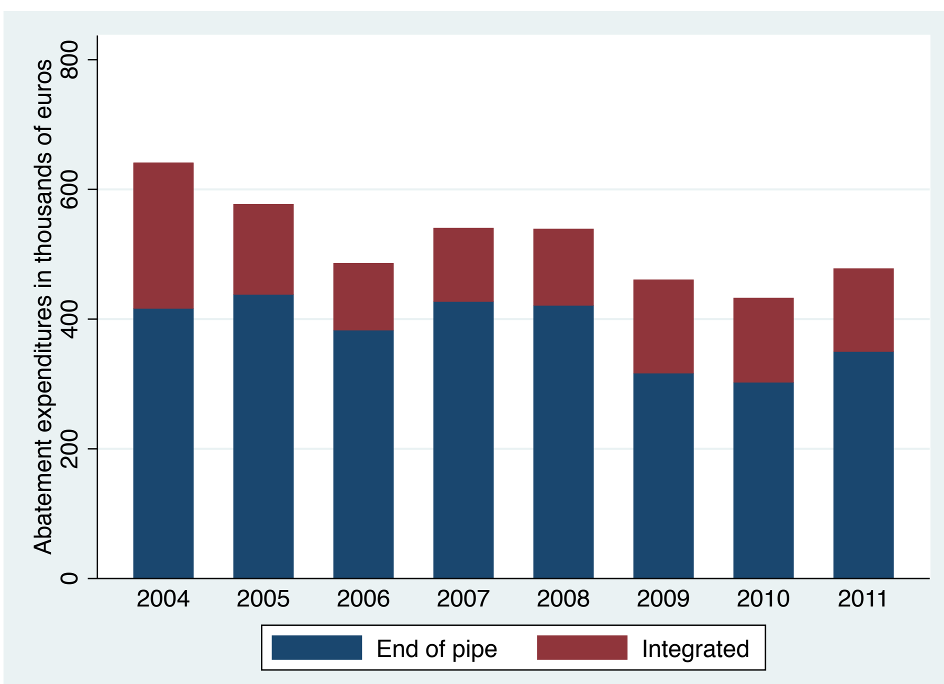
Source: elaboration based on the Annual Survey on the Resources Devoted to R&D Activities database on French firms over the period 2004-2011.

Figure 2.2: Trend of average eco-innovation of French manufacturing firms by pollution sectors (2005-2012)



Source: elaboration based on the Annual Survey on the Resources Devoted to R&D Activities database on French firms over the period 2005-2012.

Figure 2.3: Trend of average abatement expenditure of French manufacturing firms by abatement type (2004-2011)



Source: elaboration based on ANTIPOL database on French firms over the period 2004-2011.

Table 2.1: Definition of variables

Variable	Description
Dependent Variables	
TFP	total factor productivity
Operating_margin	operating profit divided by turnover
Explanatory variables	
Abatement_intensity	total abatement costs divided by total output in %
End_of_pipe	end of pipe abatement investment divided by total output in %
Integrated	integrated abatement investment divided by total output in %
Log_EnvR&D	log of green R&D expenditure
R&D_intensity	number of full-time equivalent employees dedicated to R&D divided by total number of full-time equivalent employees
ExtR&D_d	=1 if the firm is subcontracting and collaborating on R&D with external parties, 0 otherwise
Pubfunding_d	=1 if the firm received R&D resources from public sector, 0 otherwise
EMS	=1 if the firm has implemented ISO14001 or other environmental management systems, 0 otherwise
EMS_process	=1 if the firm is in the process of applying for environment management system, 0 otherwise
Log_age	log of number of years since the firm began to operate
Log_size	log of firm size (total number of full-time equivalent employees)
Log_avewage	log of average wage (total salary expenditure divided by total number of full-time equivalent employees)
HHI	Herfindahl Hirschman Index
Export_d	=1 if the firm exports, 0 otherwise
French_group	=1 if more than 50% of share of the firm is held by a French group, 0 otherwise
Foreign_group	=1 if more than 50% of share of the firm is held by a foreign group, 0 otherwise
Leverage	ratio between total liability and shareholders' equity

Table 2.2: First step estimation on the policy induced eco-innovation of French manufacturing firms (2004-2011)

	Dependent variable: $Log\_EnvR\&D_{i(t-1)}$
Abatement_intensity$_{i(t-2)}$	0.1430*
	(0.0871)
R&D_intensity$_{i(t-2)}$	0.8736
	(1.0493)
ExtR&D_d$_{i(t-2)}$	0.1976***
	(0.0788)
Pubfunding_intensity$_{i(t-2)}$	0.0540
	(0.0919)
EMS$_{i(t-2)}$	0.1624*
	(0.0937)
EMS_process$_{i(t-2)}$	-0.0892**
	(0.0474)
Log_age$_{i(t-2)}$	-0.2881
	(0.02442)
Log_size$_{i(t-2)}$	0.2567
	(0.2467)
Log_avewage$_{i(t-2)}$	0.7545***
	(0.2768)
HHI$_{i(t-2)}$	-1.0205
	(1.5309)
Export_d$_{i(t-2)}$	0.3534**
	(0.1982)
French_group$_{i(t-2)}$	0.0209
	(0.2506)
Foreign_group$_{i(t-2)}$	0.0828
	(0.2567)
Leverage$_{i(t-2)}$	-0.0147
	(0.0099)
Observations	4,851
No.firms	1,524

Coefficients reported with robust standard errors in parentheses.
Regressions include region, sectorsector and year dummies.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.3: Summary statistics for all firms

Variable	Mean	Std.Dev	Min	Max
TFP	3.3545	0.4426	1.5728	4.7451
Operating_margin	0.0723	0.1213	-2.1086	0.4225
Abatement_intensity	0.1758	0.3720	0	2.5846
End_of_pipe	0.1459	0.3282	0	2.2651
Integrated	0.0263	0.0656	0	0.4832
EnvR&D	549.86	5332.85	0	191780.4
R&D_intensity	0.0894	0.0958	0.0002	0.8421
ExtR&D_d	0.6345	0.4816	0	1
Pubfunding_d	0.2712	0.4446	0	1
EMS	0.7521	0.4318	0	1
EMS_process	0.1207	0.3258	0	1
Age	34.4656	23.7603	3	111
Size	664.611	837.344	12.5	3908
Avewage	39.0859	11.6445	17.6686	88.5162
HHI	0.0576	0.0753	0.0018	0.4149
Export_d	0.9579	0.2007	0	1
French_group	0.5084	0.4999	0	1
Foreign_group	0.4845	0.4998	0	1
Leverage	1.3723	2.7911	-11.6410	22.9539

Source: ANTIPOL, FARE, FICUS and The Annual Survey on the Resources Devoted to R&D Activities data. Unit: thousand euros. Information refers to the period 2004-2011.

Table 2.4: Effects of abatement intensity and induced eco-innovation on productivity of French manufacturing firms (2004-2011): baseline estimation

	Dependent variable: TFP		
	(Model 1) (all firms) IV	(Model 2) (all firms) IV	(Model 3) (all firms) IV
Abatement_intensity$_{i(t-1)}$	-0.0350**		
	(0.0157)		
End_of_pipe$_{i(t-1)}$		-0.0275	
		(0.0194)	
Integrated$_{i(t-1)}$		-0.2089*	
		(0.1196)	
Log_EnvR&D$_{i(t-1)}$	-0.0020	-0.0015	-0.0019
	(0.0078)	(0.0078)	(0.0077)
R&D_intensity$_{i(t-1)}$	0.1119	0.1082	0.1144
	(0.1301)	(0.1292)	(0.1299)
ExtR&D_d$_{i(t-1)}$	0.0429***	0.0433***	0.0429***
	(0.0136)	(0.0136)	(0.0136)
Pubfunding_intensity$_{i(t-1)}$	-0.0275*	-0.0270*	-0.0276*
	(0.0142)	(0.0141)	(0.0142)
EMS$_{i(t-1)}$	-0.0046	-0.0039	-0.0061
	(0.0162)	(0.0162)	(0.0162)
EMS_process$_{i(t-1)}$	0.0426**	0.0435**	0.0421**
	(0.0179)	(0.0179)	(0.0180)
Log_age$_{i(t-1)}$	-0.0041	-0.0045	-0.0033
	(0.0152)	(0.0151)	(0.0152)
Log_size$_{i(t-1)}$	0.0294***	0.0281**	0.0304***
	(0.0131)	(0.0132)	(0.0131)
Log_avewage$_{i(t-1)}$	0.3249***	0.3255***	0.3243***
	(0.0513)	(0.0512)	(0.0512)
HHI$_{i(t-1)}$	0.3254**	0.3221**	0.3263**
	(0.1487)	(0.1487)	(0.1486)
Export_d$_{i(t-1)}$	0.0398	0.0387	0.0421
	(0.0446)	(0.0449)	(0.0446)
French_group$_{i(t-1)}$	0.0192	0.0226	0.0206
	(0.0496)	(0.0494)	(0.0488)
Foreign_group$_{i(t-1)}$	0.0417	0.0448	0.0427
	(0.0511)	(0.0508)	(0.0503)
Leverage$_{i(t-1)}$	-0.0034	-0.0033	-0.0033
	(0.0022)	(0.0022)	(0.0022)
Kleibergen-Papp rk LM statistic	163.66***	163.58***	163.35***
Kleibergen-Papp Wald rk F statistic	15.853*	15.86*	15.79*
Observations	4,851	4,851	4,851
No.firms	1,524	1,524	1,524

Coefficients reported with robust standard errors in parentheses. All regressions include region, sector sector and year dummies.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.5: Effects of abatement intensity and induced eco-innovation on productivity of French manufacturing firms (2004-2011): by pollution intensity

	Dependent variable: TFP			
	(Model 1) (Polluters) IV	(Model 2) (Polluters) IV	(Model 3) (Clean firms) IV	(Model 4) (Clean firms) IV
Abatement_intensity$_{i(t-1)}$	-0.0401**		-0.0305	
	(0.0197)		(0.0258)	
End_of_pipe$_{i(t-1)}$		-0.346		-0.0206
		(0.0243)		(0.0179)
Integrated$_{i(t-1)}$		-0.2284		0.1329
		(0.1823)		(0.0822)
Log_EnvR&D$_{i(t-1)}$	-0.0084	-0.0086	-0.0009	-0.0009
	(0.0149)	(0.0149)	(0.0089)	(0.0089)
R&D_intensity$_{i(t-1)}$	0.5110*	0.5086*	0.0392	-0.0403
	(0.2854)	(0.2828)	(0.1250)	(0.1250)
ExtR&D_d$_{i(t-1)}$	0.0499	0.0510	0.0406***	0.0403***
	(0.0331)	(0.0333)	(0.0143)	(0.0143)
Pubfunding_intensity$_{i(t-1)}$	-0.0466*	-0.0460*	-0.0147	-0.0140
	(0.0273)	(0.0273)	(0.0161)	(0.0161)
EMS$_{i(t-1)}$	0.0117	0.0113	-0.0085	0.0075
	(0.0243)	(0.0241)	(0.0207)	(0.0207)
EMS_process$_{i(t-1)}$	0.0823**	0.0838***	0.0246**	0.0254
	(0.0265)	(0.0266)	(0.0232)	(0.0232)
Log_age$_{i(t-1)}$	0.0397	0.0389	-0.0224	-0.0229
	(0.0353)	(0.0351)	(0.0158)	(0.0157)
Log_size$_{i(t-1)}$	0.0244	0.0228	0.0328**	0.0317**
	(0.0228)	(0.0229)	(0.0152)	(0.0152)
Log_avewage$_{i(t-1)}$	0.2851***	0.2861***	0.3418***	0.3418***
	(0.0797)	(0.0794)	(0.0661)	(0.0661)
HHI$_{i(t-1)}$	1.1588***	1.1426***	0.1249	0.1169
	(0.4008)	(0.4023)	(0.1637)	(0.1635)
Export_d$_{i(t-1)}$	0.0646	0.0605	0.0218	0.0223
	(0.0941)	(0.0957)	(0.0392)	(0.0392)
French_group$_{i(t-1)}$	-0.0598	-0.0562	0.0747	0.0763
	(0.0700)	(0.0697)	(0.0739)	(0.0741)
Foreign_group$_{i(t-1)}$	0.0118	0.0150	0.0641	0.0657
	(0.0746)	(0.0739)	(0.0749)	(0.0749)
Leverage$_{i(t-1)}$	-0.0003	-0.0001	-0.0033	-0.0043
	(0.0038)	(0.0038)	(0.0022)	(0.0027)
Kleibergen-Papp rk LM statistic	201.50***	57.29***	121.14***	122.96***
Kleibergen-Papp Wald rk F statistic	17.19*	4.925	12.58*	12.59*
Observations	1,532	1,532	3,319	3,319
No.firms	440	440	1,084	1,084

Coefficients reported with robust standard errors in parentheses. All regressions include regional, sectoral and year dummies.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.6: Effects of abatement intensity and induced eco-innovation on profitability of French manufacturing firms (2004-2011): baseline estimation

	Dependent variable: Operating_margin		
	(Model 1) (all firms) IV	(Model 2) (all firms) IV	(Model 3) (all firms) IV
$\text{TFP}_{i(t-1)}$	0.1081***	0.1079***	0.1082***
	(0.0094)	(0.0094)	(0.0094)
$\text{Abatement\_intensity}_{i(t-1)}$	-0.0012		
	(0.4774)		
$\text{End\_of\_pipe}_{i(t-1)}$		-0.0031	
		(0.0026)	
$\text{Integrated}_{i(t-1)}$		-0.0104	
		(0.0145)	
$\text{Log\_EnvR\&D}_{i(t-1)}$	-0.0027*	-0.0027*	-0.0027*
	(0.0016)	(0.0016)	(0.0021)
$\text{R\&D\_intensity}_{i(t-1)}$	-0.0009	-0.0013	-0.0007
	(0.0371)	(0.0371)	(0.0371)
$\text{ExtR\&D\_d}_{i(t-1)}$	0.0054	0.0053	0.0054
	(0.0046)	(0.0047)	(0.0046)
$\text{Pubfunding\_d}_{i(t-1)}$	0.0007	0.0007	0.0007
	(0.0036)	(0.0036)	(0.0036)
$\text{EMS}_{i(t-1)}$	0.0051	0.0053	0.0051
	(0.0039)	(0.0114)	(0.0039)
$\text{EMS\_progression}_{i(t-1)}$	0.0113***	0.0114***	0.0113***
	(0.0039)	(0.0038)	(0.0039)
$\text{Log\_age}_{i(t-1)}$	0.0084**	0.0082**	0.0085**
	(0.0035)	(0.0035)	(0.0035)
$\text{Log\_size}_{i(t-1)}$	0.0004	0.0002	0.0005
	(0.0029)	(0.0029)	(0.0029)
$\text{Log\_avewage}_{i(t-1)}$	-0.0369*	-0.0369*	-0.0371*
	(0.0190)	(0.0190)	(0.0190)
$\text{HHI}_{i(t-1)}$	-0.0019	-0.0018	-0.0019
	(0.0446)	(0.0447)	(0.0446)
$\text{Export\_d}_{i(t-1)}$	-0.0035	-0.0039	-0.0034
	(0.0099)	(0.0100)	(0.0100)
$\text{French\_group}_{i(t-1)}$	0.0013	0.0008	0.0013
	(0.0092)	(0.0094)	(0.0092)
$\text{Foreign\_group}_{i(t-1)}$	-0.0046	-0.0052	-0.0046
	(0.0097)	(0.0099)	(0.0097)
$\text{Leverage}_{i(t-1)}$	-0.0030***	-0.0030***	-0.0030***
	(0.0009)	(0.0009)	(0.0009)
Kleibergen-Papp rk LM statistic	245.775***	245.192***	247.984***
Kleibergen-Papp Wald rk F statistic	25.365**	25.704*	25.317**
Observations	4,071	4,071	4,071
No.firms	1,471	1,471	1,471

Coefficients reported with robust standard errors in parentheses. All regressions include region, sector sector and year dummies.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.7: Effects of abatement intensity and induced eco-innovation on profitability of French manufacturing firms (2004-2011): by pollution intensity

	Dependent variable: Operating_margin			
	(Model 1) (Polluters) IV	(Model 2) (Polluters) IV	(Model 3) (Clean firms) IV	(Model 4) (Clean firms) IV
$\text{TFP}_{i(t-1)}$	0.1168***	0.1157***	0.1049***	0.1047***
	(0.0139)	(0.0139)	(0.0121)	(0.0121)
$\text{Abatement\_intensity}_{i(t-1)}$	0.0005		-0.4287	
	(0.0058)		(0.9166)	
$\text{End\_of\_pipe}_{i(t-1)}$		-0.0032		0.0023
		(0.0028)		(0.0100)
$\text{Integrated}_{i(t-1)}$		0.0015		-0.0593
		(0.0159)		(0.0412)
$\text{Log\_EnvR\&D}_{i(t-1)}$	-0.0022	-0.0019	-0.0031*	-0.0030*
	0.0029	(0.0029)	(0.0018)	(0.0018)
$\text{R\&D\_intensity}_{i(t-1)}$	0.1458**	0.1443**	-0.0642	-0.0643
	(0.0617)	(0.0617)	(0.0456)	(0.0456)
$\text{ExtR\&D\_d}_{i(t-1)}$	0.0038	0.0032	0.0056	0.0056
	(0.0089)	(0.0091)	(0.0054)	(0.0054)
$\text{Pubfunding\_d}_{i(t-1)}$	0.0005	0.0004	-0.0006	-0.0003
	(0.0066)	(0.0066)	(0.0043)	(0.0043)
$\text{EMS}_{i(t-1)}$	-0.0049	-0.0047	0.0127***	0.0131***
	(0.0072)	(0.0072)	(0.0046)	(0.0046)
$\text{EMS\_process}_{i(t-1)}$	0.0170**	0.0171**	0.0080*	0.0083**
	(0.0079)	(0.0079)	(0.0042)	(0.0042)
$\text{Log\_age}_{i(t-1)}$	0.0099	0.0095	0.0087**	0.0086**
	(0.0077)	(0.0078)	(0.0037)	(0.0037)
$\text{Log\_size}_{i(t-1)}$	0.0073	0.0071	-0.0031	-0.0035
	(0.0049)	(0.0049)	(0.0036)	(0.0036)
$\text{Log\_avewage}_{i(t-1)}$	-0.0557**	-0.0552**	-0.0301	-0.0301
	(0.0275)	(0.0273)	(0.0242)	(0.0242)
$\text{HHI}_{i(t-1)}$	0.1641	0.1673	-0.0226	-0.0231
	(0.1143)	(0.1161)	(0.0494)	(0.0495)
$\text{Export\_intensity}_{i(t-1)}$	-0.0179	-0.0179	0.0063	0.0071
	(0.0144)	(0.0144)	(0.0133)	(0.0133)
$\text{French\_group}_{i(t-1)}$	0.0098	0.0081	-0.0209**	-0.0196**
	(0.0143)	(0.0147)	(0.0088)	(0.0090)
$\text{Foreign\_group}_{i(t-1)}$	-0.0025	0.0039	-0.0228**	-0.0216**
	(0.0144)	(0.0148)	(0.0100)	(0.0101)
$\text{Leverage}_{i(t-1)}$	-0.0053**	-0.0053**	-0.0021***	-0.0022***
	(0.0026)	(0.0027)	(0.0006)	(0.0006)
Kleibergen-Papp rk LM statistic	91.371***	91.27***	179.13***	179.41***
Kleibergen-Papp Wald rk F statistic	11.38*	10.411*	25.67*	24.29*
Observations	1,287	1,287	2,784	2,784
No.firms	432	432	1,039	1,039

Coefficients reported with robust standard errors in parentheses. All regressions include regional, sectoral and year dummies.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8: Effects of abatement intensity and induced eco-innovation on productivity of French manufacturing firms (2004-2011): baseline model for different thresholds regarding aggregation process

	Dependent variable: TFP		
	(0%)	(50%)	(75%)
	IV	IV	IV
Abatement_intensity$_{i(t-1)}$	-0.0350**	-0.0366**	-0.0331**
	(0.0157)	(0.0165)	(0.0171)
Log_EnvR&D$_{i(t-1)}$	-0.0020	-0.0018	-0.0012
	(0.0078)	(0.0083)	(0.0094)
R&D_intensity$_{i(t-1)}$	0.1119	0.1146	0.0985
	(0.1301)	(0.1402)	(0.1488)
ExtR&D_d$_{i(t-1)}$	0.0429***	0.0339**	0.0321**
	(0.0136)	(0.0144)	(0.0147)
Pubfunding_intensity$_{i(t-1)}$	-0.0275*	-0.0223	-0.0174
	(0.0142)	(0.0139)	(0.0145)
EMS$_{i(t-1)}$	-0.0046	0.0056	0.0094
	(0.0162)	(0.0172)	(0.0170)
EMS_process$_{i(t-1)}$	0.0426**	0.0359*	0.0359*
	(0.0179)	(0.0200)	(0.0204)
Log_age$_{i(t-1)}$	-0.0041	0.0001	-0.0005
	(0.0152)	(0.0157)	(0.0167)
Log_size$_{i(t-1)}$	0.0294***	0.0216	0.0195
	(0.0131)	(0.0142)	(0.0155)
Log_avewage$_{i(t-1)}$	0.3249***	0.3491***	0.3446***
	(0.0513)	(0.0525)	(0.0569)
HHI$_{i(t-1)}$	0.3254**	0.3327**	0.3394**
	(0.1487)	(0.1534)	(0.1659)
Export_d$_{i(t-1)}$	0.0398	0.0480	0.0511
	(0.0446)	(0.0463)	(0.0483)
French_group$_{i(t-1)}$	0.0192	-0.0118	-0.0022
	(0.0496)	(0.0494)	(0.0578)
Foreign_group$_{i(t-1)}$	0.0417	0.0052	0.0205
	(0.0511)	(0.0512)	(0.0591)
Leverage$_{i(t-1)}$	-0.0034	-0.0025	-0.0028
	(0.0022)	(0.0023)	(0.0023)
Kleibergen-Papp rk LM statistic	202.29***	150.49***	140.68***
Kleibergen-Papp Wald rk F statistic	16.32*	14.38*	12.83*
Observations	4,851	4,331	3,792
No.firms	1,524	1,437	1,326

Coefficients reported with robust standard errors in parentheses. All regressions include region, sector sector and year dummies.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.9: Firm distribution for threshold 0% level and threshold 75% level

		0% threshold		75% threshold	
Nace code	Description	Number of firms	Percentage in %	Number of firms	Percentage in %
15	Food products and beverages	99	8.95	85	7.83
17	Textiles	48	3.25	45	3.58
18	Wearing apparel, dressing and dying of fur	5	0.41	2	0.18
19	Leather, leather products and footwear	5	0.54	5	0.66
20	Wood and products of wood and cork	16	1.04	16	1.31
21	Pulp, paper and paper products	25	1.94	24	1.91
22	Printing and publishing	6	0.41	4	0.42
23	Coke, refined petroleum products and nuclear fuel	10	0.59	9	0.59
24	Chemicals and chemical products	295	17.13	236	15.83
25	Rubber and plastics products	138	9.13	127	9.92
26	Other non-metallic mineral products	52	3.03	40	2.27
27	Basic metals	58	3.52	54	3.88
28	Fabricated metal products, except machinery and equipment	114	8.90	104	9.56
29	Machinery and equipment, n.e.c.	231	14.32	205	15.23
30	Office machinery and computers	4	0.54	4	0.36
31	Electrical machinery and apparatus, n.e.c	104	6.51	92	6.15
32	Radio, television and communication equipment and apparatus	57	3.66	48	3.76
33	Medical, precision and optical instruments, watches and clocks	98	6.64	82	6.39
34	Motor vehicles, trailers and semi-trailers	74	4.25	70	4.78
35	Other transport equipment	42	2.35	39	2.69
36	Manufacturing n.e.c	35	2.44	29	2.27
40	Electricity, gas and water supply	8	0.45	6	0.42
total		1,524	100	1,326	100

Table 2.10: Effects of abatement intensity and induced eco-innovation on profitability of French manufacturing firms (2004-2011): baseline model for different thresholds regarding aggregation process

	Dependent variable: Operating_margin		
	(Model 1) (0%) IV	(Model 2) (50%) IV	(Model 3) (75%) IV
$TFP_{i(t-1)}$	0.1081***	0.1140***	0.1089***
	(0.0094)	(0.0108)	(0.0120)
$Abatement\_intensity_{i(t-1)}$	-0.0012	-0.4346	-0.4830
	(0.4774)	(0.4857)	(0.5173)
$Log\_EnvR\&D_{i(t-1)}$	-0.0027*	-0.0032*	-0.0024*
	(0.0016)	(0.0017)	(0.0017)
$R\&D\_intensity_{i(t-1)}$	-0.0009	-0.0161	-0.0311
	(0.0371)	(0.0368)	(0.0399)
$ExtR\&D\_d_{i(t-1)}$	0.0054	0.0067	0.0064
	(0.0046)	(0.0049)	(0.0055)
$Pubfunding\_d_{i(t-1)}$	0.0007	0.0015	0.0031
	(0.0036)	(0.0036)	(0.0040)
$EMS_{i(t-1)}$	0.0051	0.0088**	0.0082*
	(0.0039)	(0.0041)	(0.0045)
$EMS\_progression_{i(t-1)}$	0.0113***	0.0095**	0.0103**
	(0.0039)	(0.0042)	(0.0047)
$Log\_age_{i(t-1)}$	0.0084**	0.0081**	0.0077**
	(0.0035)	(0.0035)	(0.0038)
$Log\_size_{i(t-1)}$	0.0004	-0.0033	-0.0025
	(0.0029)	(0.0028)	(0.0030)
$Log\_avewage_{i(t-1)}$	-0.0369*	-0.0499***	-0.0435**
	(0.0190)	(0.0175)	(0.0192)
$HHI_{i(t-1)}$	-0.0019	0.0047	-0.0066
	(0.0446)	(0.0473)	(0.0552)
$Export\_d_{i(t-1)}$	-0.0035	-0.0013	-0.0027
	(0.0099)	(0.0135)	(0.0149)
$French\_group_{i(t-1)}$	0.0013	0.0052	0.0003
	(0.0092)	(0.0104)	(0.0121)
$Foreign\_group_{i(t-1)}$	-0.0046	0.0007	-0.0056
	(0.0097)	(0.0109)	(0.0125)
$Leverage_{i(t-1)}$	-0.0030***	-0.0031***	-0.0033***
	(0.0009)	(0.0009)	(0.0010)
Kleibergen-Papp rk LM statistic	202.29***	231.24***	219.65***
Kleibergen-Papp Wald rk F statistic	16.32*	30.91*	27.47*
Observations	4,851	3,602	3,134
No.firms	1,524	1,369	1,251

Coefficients reported with robust standard errors in parentheses. All regressions include region, sector sector and year dummies.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.11: Effects of abatement intensity and induced eco-innovation on profitability of French manufacturing firms (2004-2011): GMM estimation

	Dependent variable: TFP		
	(Model 1) (all firms) GMM	(Model 2) (all firms) GMM	(Model 3) (all firms) GMM
$TFP_{i(t-1)}$	0.8044***	0.8910***	0.8911***
	(0.0121)	(0.1299)	(0.1308)
Abatement_intensity$_{i(t-1)}$	-0.0169*		
	(0.0088)		
End_of_pipe$_{i(t-1)}$		-0.0079	
		(0.0134)	
Integrated$_{i(t-1)}$		-0.1279*	
		(0.0763)	
Log_EnvR&D$_{i(t-1)}$	0.0146	-0.0017	-0.0019
	(0.0167)	(0.0015)	(0.0015)
R&D_intensity$_{i(t-1)}$	0.8436*	0.8189*	0.8499*
	(0.4350)	(0.4356)	(0.4364)
ExtR&D_d$_{i(t-1)}$	0.0037	0.0043	0.0042
	(0.0122)	(0.0124)	(0.0124)
Pubfunding_d$_{i(t-1)}$	-0.0252*	-0.0245*	-0.0263*
	(0.0149)	(0.0149)	(0.0151)
EMS$_{i(t-1)}$	0.0027	0.0034	0.0013
	(0.0079)	(0.0079)	(0.0079)
EMS_process$_{i(t-1)}$	0.0117	0.0123	0.0114
	(0.0211)	(0.0211)	(0.0212)
Log_age$_{i(t-1)}$	-0.0005	-0.0008	-0.0002
	(0.0052)	(0.0052)	(0.0052)
Log_size$_{i(t-1)}$	0.0132**	0.0123**	0.0137***
	(0.0051)	(0.0051)	(0.0051)
Log_avewage$_{i(t-1)}$	-0.1714	-0.1647	-0.1688
	(0.1328)	(0.1348)	(0.1348)
HHI$_{i(t-1)}$	-0.0171	-0.0127	-0.0167
	(0.0889)	(0.0893)	(0.0897)
Export_d$_{i(t-1)}$	0.0198	0.0196	0.0215
	(0.0202)	(0.0201)	(0.0204)
French_group$_{i(t-1)}$	-0.0139	-0.0126	-0.0147
	(0.0172)	(0.0173)	(0.0173)
Foreign_group$_{i(t-1)}$	0.0104	0.0109	0.0099
	(0.0202)	(0.0201)	(0.0203)
Leverage$_{i(t-1)}$	-0.0031*	-0.0031*	-0.0031*
	(0.0018)	(0.0018)	(0.0018)
AR(2) p value	0.678	0.674	0.669
Hansen p value	0.112	0.113	0.111
Observations	6,838	6,838	6,838
No.firms	2,017	2,017	2,017

Coefficients reported with robust standard errors in parentheses. All regressions include region, sector sector and year dummies.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.12: Effects of abatement intensity and induced eco-innovation on profitability of French manufacturing firms (2004-2011): GMM estimation

	Dependent variable: Operating_margin		
	(Model 1) (all firms) GMM	(Model 2) (all firms) GMM	(Model 3) (all firms) GMM
Operating_margin$_{i(t-1)}$	0.0722	0.0711	0.0693
	(0.1282)	(0.1292)	(0.1197)
TFP$_{i(t-1)}$	0.0892***	0.0782***	0.0812***
	(0.0323)	(0.0311)	(0.0277)
Abatement_intensity$_{i(t-1)}$	0.0093		
	(0.0074)		
End_of_pipe$_{i(t-1)}$		-0.0048	
		(0.0076)	
Integrated$_{i(t-1)}$		-0.0037	
		(0.0060)	
Log_EnvR&D$_{i(t-1)}$	-0.0005*	-0.0003*	-0.0014*
	(0.0002)	(0.0001)	(0.0019)
R&D_intensity$_{i(t-1)}$	-0.1004	0.1135	0.1284
	(0.2416)	(0.2612)	(0.1922)
ExtR&D_d$_{i(t-1)}$	-0.0033	0.0072	0.0029
	(0.0109)	(0.0147)	(0.0128)
Pubfunding_d$_{i(t-1)}$	-0.0122*	-0.0114*	-0.0028
	(0.0078)	(0.0065)	(0.0062)
EMS$_{i(t-1)}$	0.0093	-0.0037	0.0026
	(0.0096)	(0.0185)	(0.0106)
EMS_process$_{i(t-1)}$	0.0024	0.0026	0.0091
	(0.0079)	(0.0069)	(0.0111)
Log_age$_{i(t-1)}$	0.0059	0.0034	0.0068
	(0.0254)	(0.0285)	(0.0052)
Log_size$_{i(t-1)}$	0.0013	0.0020	0.0011
	(0.0335)	(0.0375)	(0.0285)
Log_avewage$_{i(t-1)}$	-0.0426	-0.0776	0.0773
	(0.0446)	(0.0241)	(0.0376)
HHI$_{i(t-1)}$	-0.1479	-0.1348	-0.1247
	(0.0672)	(0.0869)	(0.0934)
Export_d$_{i(t-1)}$	-0.0419	0.0585	0.0287
	(0.0316)	(0.0412)	(0.0206)
French_group$_{i(t-1)}$	0.0023	0.0025	0.0033
	(0.0190)	(0.0153)	(0.0096)
Foreign_group$_{i(t-1)}$	0.0183	0.0111	0.0102
	(0.0241)	(0.0288)	(0.0303)
Leverage$_{i(t-1)}$	-0.0016*	-0.0016*	-0.0020*
	(0.0009)	(0.0009)	(0.0010)
AR(2) p value	0.0007	0.0007	0.0008
Hansen p value	0.508	0.462	0.267
Observations	3,368	6,838	6,838
No.firms	1,453	2,017	2,017

Coefficients reported with robust standard errors in parentheses. All regressions include region, sector sector and year dummies.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.13: Effects of abatement intensity and induced eco-innovation on productivity of French manufacturing firms (2004-2011): different measurements for TFP

	Dependent variable: TFP		
	(Model 1) TFP (all firms) IV	(Model 2) (TFP_lp) (all firms) IV	(Model 3) (TFP_wooldridge) (all firms) IV
Abatement_intensity$_{i(t-1)}$	-0.0342**	-0.0327**	-0.0343**
	(0.0156)	(0.0151)	(0.0157)
Log_EnvR&D$_{i(t-1)}$	-0.0042	-0.0034	-0.0014
	(0.0074)	(0.0075)	(0.0077)
R&D_intensity$_{i(t-1)}$	0.0637	0.1203	0.1221
	(0.1049)	(0.1288)	(0.1309)
ExtR&D_d$_{i(t-1)}$	0.0379***	0.0422***	0.0437***
	(0.0130)	(0.0129)	(0.0136)
Pubfunding_d$_{i(t-1)}$	-0.0251*	-0.0314**	-0.0274**
	(0.0137)	(0.0145)	(0.0141)
EMS$_{i(t-1)}$	-0.0037	-0.0026	-0.0045
	(0.0154)	(0.0155)	(0.0162)
EMS_progcess$_{i(t-1)}$	0.0404**	0.0415**	0.0428**
	(0.0169)	(0.0172)	(0.0179)
Log_age$_{i(t-1)}$	-0.0095	-0.0017	-0.0016
	(0.0139)	(0.0146)	(0.0151)
Log_age$_{i(t-1)}$	-0.0334	-0.0017	-0.0016
	(0.0111)	(0.0146)	(0.0151)
Log_avewage$_{i(t-1)}$	0.3153***	0.3498***	0.3399***
	(0.0483)	(0.0499)	(0.0512)
HHI$_{i(t-1)}$	0.3416**	0.3409**	0.3645**
	(0.1473)	(0.1464)	(0.1504)
Export_d$_{i(t-1)}$	0.0297	0.0376	0.0426
	(0.0353)	(0.0412)	(0.0450)
French_group$_{i(t-1)}$	0.0153	0.0227	0.0222
	(0.0496)	(0.0476)	(0.0492)
Foreign_group$_{i(t-1)}$	0.0389	0.0453	0.0471
	(0.0509)	(0.0493)	(0.0507)
Leverage$_{i(t-1)}$	-0.0031	-0.0031	-0.0035
	(0.0022)	(0.0021)	(0.0022)
Kleibergen-Papp rk LM statistic	164.28***	166.49***	166.26***
Kleibergen-Papp Wald rk F statistic	15.78*	16.04*	16.06*
Observations	4,851	4,855	4,852
No.firms	1,524	1,526	1,525

Coefficients reported with robust standard errors in parentheses. All regressions include region, sector sector and year dummies.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Chapter 3

Can we invent a cleaner future: Carbon emissions and the role of eco-innovation

Abstract

In this chapter we examine the impact of eco-innovation on firm environmental performance using a firm-level panel data of French manufacturing firms that invest in R&D during 2005-2012. More specifically, we measure environmental performance using two indicators: CO_2 emissions intensity and fossil fuel intensity and estimate the effect of eco-innovation on environmental performance using the generalized method of moments (GMM) technique. In addition, we use propensity score matching and difference in difference (PSM-DiD) technique to test the effectiveness of eco-innovation in emission reduction. Our results suggest that neither CO_2 emissions intensity nor fossil fuel intensity is significantly reduced by eco-innovation. Meanwhile, comparing to firms that never invest in eco-innovation, new eco-innovators do not seem to emit less or shift energy structures. Policy implications are discussed.

Keywords: Eco-Innovation, France, Carbon Emissions, Energy

3.1 Introduction

Economic development and the accompanied pollution has caused an increase in global temperature which significantly affects the climate change. One of the primary targets is to reduce carbon emissions. Under the Kyoto Protocol, France has committed to cut its combined emissions to 5% below its 1990 level. Firms are playing a key role in reducing carbon emissions. A number of tools for reducing carbon emissions have been discussed. First, improving energy efficiency has been shown to be an effective way of reducing carbon emissions (Buchanan and Honey, 1994). Moreover, López-Peña et al. (2012) argue that to achieve carbon emission reduction, energy efficiency improvements would be more cost-effective than subsidies for renewable energy. Similarly, Chang et al. (2008) find that the adjustment in energy consumption patterns is a crucial aspect in reducing carbon emissions. Other mechanisms by which emissions may be reduced are through trade (Peters et al., 2012) or foreign direct investment (Cole et al., 2013; Lee, 2013).

Another channel by which emissions are thought to be reduced is through innovation (Dechezleprêtre et al., 2011; Su and Moaniba, 2017). Arguably, innovation-driven efficiency gains could reduce emissions and at the same time enhance economic performance. However, it remains unclear how innovation reduce emissions and to what extent. In particular, firms' incentives for research and development (R&D) investment are mainly on developing technological capabilities and ensure its future advantage, moreover firms' technological capabilities are essential to gain competitive advantage(Teece, 1986). However, only little attention has been paid to the field of emission reduction technology due to the high initial cost, thus R&D intensity may not be effective for carbon emission reduction (Jiao et al., 2018). Mensah et al. (2018) suggest a minor impact of innovation on CO2 abatement in OECD countries and particularly for France, their results report a rise in carbon emissions due to the increase in the number of patent applications received from foreign applicants. Albino et al. (2014) further argue that even for the U.S and European countries which represent the most innovative countries, there are no significant decline in emissions as innovation advances.

The purpose of this chapter is to investigate whether investing in eco-innovation allows firms to meet their environmental targets and more specifically, we investigate whether eco-innovation is effective in enhancing firms' environmental performance. The benefit of eco-innovation is that it provides firms with the opportunity to ease environmental pressures and at the same time promote sustainable economic growth through the more efficient use of resources (Costa-Campi et al., 2017).[1] While the previous literature has paid close attention to the determinants of eco-innovation (Del Río et al., 2011; Cuerva et al., 2014; Del Río et al., 2017) and the impact of regulation-induced eco-innovation on economic competitiveness (Greenstone et al., 2012; Ghisetti and Rennings, 2014; Rassier and Earnhart, 2015), less attention has been devoted to examine the real impact of eco-innovation on en-

[1] There are a number of different definitions of eco-innovation. Kemp (2010) defines eco-innovation as the "production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organization (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives". In contrast, Rennings et al. (2006) views eco-innovation as "measures of relevant actors which develop new ideas, behavior, products and processes, and apply or introduce them, and contribute to a reduction of environmental burdens or to ecologically specified sustainability targets".

vironmental performance and the mechanisms through which such an effect may take place.

In this study, we investigate whether eco-innovation can improve the environmental performance of firms, taking different aspects of environmental performance into consideration. We use green R&D expenditure to measure eco-innovation and we measure environmental performance in two ways, first CO_2 emissions intensity and second, fossil fuel intensity. We define eco-innovation as the internal R&D expenditure dedicated to the protection of the environment. The contribution of this chapter is three-fold. First, previous studies investigating the relationship between eco-innovation and environmental performance (Lee and Min, 2015; Zhang et al., 2017) tend to use only one indicator of environmental performance which is usually CO_2 emissions intensity at the industry or regional-level (Huaman and Jun, 2014; Picazo-Tadeo et al., 2014; Costantini et al., 2017). In this chapter, we employ an additional measure that takes into account the energy mix optimization. Second, our empirical analysis is based on a unique data set at the firm level which provides detailed information on French manufacturing firms' innovation activities and energy consumption between 2005 and 2012. Such data allows us to investigate the effectiveness of eco-innovation across industries in France. Thus instead of focusing on just one industry like previous firm-level studies (Zhao et al., 2015; Fernando and Wah, 2017), our sample comprises innovative firms across 20 different manufacturing industries to identify whether the decision to invest in eco-innovation subsequently affects a firm's environmental performance. Third, we apply a range of econometric techniques including system generalized method of moments (GMM) and a propensity score matching difference in difference (SPM-DiD) approach to provide a precise examination of the effectiveness of eco-innovation. System GMM approach provides an efficient estimation that takes the dynamic effect of environmental performance into consideration. Furthermore, to control for the potential selection bias, we employ a PSM-DiD method.

To briefly summarize our results, our results suggest that eco-innovation does not exhibit a significant enhancement effect on environmental performance for French manufacturing firms over the period 2005-2012. First, our findings suggest that the decision to invest in eco-innovation does not significantly reduce firm's CO_2 emissions intensity. Meanwhile, investing in general R&D does not significantly reduce CO_2 emissions intensity either. In particular, larger and more mature firms are more likely to have lower CO_2 emissions intensity. Regarding fossil fuel intensity, we do not find any evidence that eco-innovation significantly reduces fossil fuel intensity. However, results suggest that more productive firms in non pollution intensive sectors are likely to reduce their fossil fuel intensity. Moreover, investing in general R&D would also reduce fossil fuel intensity significantly.

Furthermore, when we analyse the change in CO_2 emissions intensity of French manufacturing firms that begin to invest in eco-innovation, we find that relative to a control group, the CO_2 emissions intensity of new eco-innovators is not statistically different in the year when they start investing in eco-innovation. Similar insignificant treatment effects are observed in the next one, two and three years. After splitting firms into pollution intensive firms and non pollution intensive firms, we find that CO_2 emissions intensity is not significantly reduced after they start investing in eco-innovation for both groups. Regarding fossil fuel intensity, we do not find significant treatment effect for new eco-innovators in the year and afterward when they start investing in eco-innovation either.

The remainder of this chapter is organized as follows: Section 2 presents our a brief literature review of both the theoretical and empirical analysis of the impact of eco-innovation on environmental performance. Section 3 presents our empirical strategy and section 4 provides a comprehensive description of the data set. Section 5 discusses our results. The final section concludes.

3.2 literature Review

Among studies on eco-innovation, a large stream of existing literature investigates the determinants of eco-innovation, identifying factors such as technological push, regulatory pull and market-driven demand (De Marchi, 2012; Horbach et al., 2012; Ghisetti et al., 2015a; Hojnik and Ruzzier, 2016) in stimulating eco-innovation. Research tends to address the importance of policy interventions in stimulating eco-innovation and the intuition behind policy intervention to stimulate eco-innovation depends on the expectation that eco-innovation has a positive effect on emissions control. By investing in eco-innovation, a firm's environmental performance may improve where environmental performance is defined as the environmental impact that the corporation's activity has on the natural environment. Environmental performance includes a reduction of air emissions, waste water, solid wastes, or a decrease of consumption of hazardous/harmful/toxic materials, or a decrease in the frequency of environmental accidents and resource use reductions (Zhu and Sarkis, 2004; Aragón-Correa et al., 2008). In this study, we use CO_2 emissions intensity and fossil fuel intensity as the proxy for environmental performance.

A number of previous empirical studies have evaluated environmental performance measured as the ratio between emissions and value added (Huaman and Jun, 2014; Cruz and Dias, 2016). Due to the lack of firm-level emissions data, existing literature mainly focuses on country, region and sector-level data and exploited data from environmental hybrid economic-environmental accounting matrixes. Using a structural decomposition method to analyse industries in Taiwan during 1984–2004, Chang et al. (2008) identify the major causes of the industrial CO_2 emissions reduction and highlight that optimal energy demanding structure is more effective in carbon emissions reduction. The authors illustrate that certain industries including the highway, petrochemical materials, and steel and iron industries are the primary contributors to carbon emissions. Similarly, from a cost minimization perspective, investigating the Spanish energy sector, López-Peña et al. (2012) emphasize the important role of energy efficiency for reducing carbon emissions in the short and medium term.

In terms of the impact of innovation on curbing emissions: focusing on general innovation activities, Cole et al. (2013) find that for Japanese manufacturing firms, R&D expenditure is a key factor in the CO_2 emissions reduction. Innovation is often assumed to lead to greater efficiency of resource use which means fewer resources being used as inputs and hence less pollution emitted per unit of output while everything else equal. Yin et al. (2015) test the role of technological process in intermediating the impact of economic growth on environmental performance for Chinese provinces and find that R&D expenditures limit CO_2 emission. Similarly, Costantini et al. (2013) study the impact of internal R&D and inter-regional technological and environmental spillovers in Italian regions, and find that the spillovers effects are more important than sector internal R&D for improving environmental performance. Fernández et al. (2018) analyze the CO_2 emissions in the EU and the U.S and suggest that R&D expenditures contribute positively to the reduction of CO_2 emissions in the EU and the U.S.

Eco-innovation as a distinct from general innovation, may reduce the cost of environmental protection and could be more important for correcting pollution externalities. However, there are very few empirical studies that investigate the effectiveness of eco-innovation in achieving environmental goals. The target for firms investing in eco-innovation is to produce less waste, consume fewer resources and energy and meanwhile be productive or profitable. To engage in eco-innovation, firms need to make a long-term commitment in term of R&D investment for new environmental technologies (Roome, 1994). R&D activities on eco-innovation often center on improving the use of internal resources and capabilities to reduce environmental impacts. Adopting eco-innovation, firms tend to improve productivity and efficiency and to reduce costs and environmental impacts. However, the economic benefits from pollution reduction are often underestimated (King and Lenox, 2002). The undervaluation comes from the potentially high cost of eco-innovation. Thus firms' green capabilities are not fully exploited.

Recent empirical studies have been able to identify the positive effect of eco-innovation on environmental performance. At the country level, Huaman and Jun (2014) suggest that investing in carbon capture and storage (CCS) technologies is important to reduce future carbon emissions. By investigating the distribution of CO_2 emissions intensity, the authors argue that CCS technologies allow the continued use of non-renewable resources such as coal, which continue to provide a large percentage of energy in developing countries. Particularly focusing on 28 countries within the European Union, Picazo-Tadeo et al. (2014) examine the determinants of intertemporal environmental performance measured by greenhouse gas emissions (GHG). By taking a Data Envelopment Analysis (DEA) approach together with directional distance functions, they illustrate that the GHG had significantly decreased during the period 1990-2011. They suggest that this improvement in environmental performance is mainly due to environmental technical progress while eco-efficiency is relatively ineffective.[2]. A later study by Beltrán-Esteve and Picazo-Tadeo (2017) reach a similar conclusion that environmental technical progress is the main driver of environmental performance enhancement in EU countries. The authors further stress the essential role of environmental policies aimed at boosting catching-up in improving environmental performance, specifically for newer members that joined the EU after 2004.

[2]The concept of eco-efficiency emerged in the 1990s as a practical approach to the more encompassing concept of sustainability (Schaltegger and Thomas, 1996). The definition for eco-efficiency is that the ability of firms, industries or economies to produce goods and services while incurring less impact on the environment and consuming fewer natural resources(Picazo-Tadeo et al., 2012). It is often measured by the ratio of economic value added to environmental damage (Korhonen and Luptacik, 2004)

At the regional level, Ghisetti and Quatraro (2017) investigate eco-innovation in vertical integrated sectors in Italy in 2005, and the authors generate an indicator of environmental productivity by scaling turnover by total emissions. They conclude that eco-innovation measured by green patents, as well as spillovers from vertically related sectors, has a positive effect on environmental performance. Furthermore, the influence of eco-innovation on environmental performance is influenced by the derived demand for green technologies. Focusing on China's 30 provinces during the period 2000-2013, Zhang et al. (2017) suggest that eco-innovation significantly reduces carbon emissions. Specifically eco-innovation that improves energy efficiency appears to have the largest impact on carbon emissions abatement whereas R&D investment input and patents output also play important roles. In addition, government environmental policies do curb carbon emissions reduction, however, a lag effect is noted.

At the sector level, instead of only focusing on CO_2 emissions, a study by Carrión-Flores and Innes (2010) identify bi-directional causal links between eco-innovation and toxic air pollution in 137 manufacturing industries in the U.S. The authors find that eco-innovation is an important determinant in reducing toxic emissions, and on the other hand, tightened pollution targets also stimulate eco-innovation. Specifically focusing on the transport industry, Beltrán-Esteve and Picazo-Tadeo (2015) suggest that across 38 countries for the period 1995–2009, there has been a significant enhancement in environmental performance due to eco-innovation and this enhancement is relatively stronger in low- and middleincome economies. The authors decompose environmental performance into environmental technical change and eco-efficiency change, which assesses the direct impact of developing eco-innovation and catching-up with best available green technologies, respectively. The results suggest that comparing with catching-up approach, development of green technologies is the main driver of the enhanced environmental performance. Meanwhile, considering both generation and diffusion of eco-innovation, Costantini et al. (2017) find a significant effect of eco-innovation on reducing local environmental impact of production across 14 manufacturing sectors in 27 EU members. They further suggest that along with the direct effect of eco-innovation on environmental performance, eco-innovation si also able to reduce environmental impact of other sectors in other location through market transactions such as sustainable supply chain.

At the firm level, focusing on manufacturing firms in Japan, Lee and Min (2015) examine the impact of environmental R&D investments on carbon emissions and find that environmental R&D reduces carbon emissions and increases firms' profitability. The authors stress the importance of corporate management strategies which provide excessive organizational capabilities, in order to implement proactive environmental practices which enhance environmental and financial performance. However, this study fails to control for the influence of national environmental regulations in Japan using OLS estimation, this could lead to potentially biased results. Küçükoğlu and Pınar (2015) surveyed top 500 firms in Turkey and find that eco-innovation activities have significant positive effect on a company's environmental performance. The authors stress the importance of green process innovation in enhancing firm environmental performance. Zhao et al. (2015) distinguish between three environmental policies on efficiency improvement, namely command and control regulations, market-based regulations, and government subsidies. The authors suggest that government subsidies for new technological R&D reduce CO_2 emissions for Chinese power plants. Focusing on Korean-owned firms in Jiangsu province in China, Long et al. (2017a) find that eco-innovation significantly improves firm environmental performance and furthermore, the magnitude of this positive effect is greater than economic performance. Especially for product eco-innovation, a significant and positive effect is noted. Moreover, using data collected from 182 Chinese firms in 2016, Long et al. (2017b) adopt the theory of planned behavior model and find that in general, eco-innovation improves firm environmental performance. The authors further decompose eco-innovation into four dimensions, namely product design, raw material, production processes and waste treatment. Their results show that only production processes and waste treatment significantly enhance firm environmental performance. For Malaysian firms in green technology sector, Fernando and Wah (2017) confirm the positive effect of eco-innovation on environmental performance. Their results suggest that stricter regulations and market orientation on cleaner products also improve firm environmental performance.

To sum up, the existing literature has shed some light on the impact of eco-innovation on environment protection and economic development, however current empirical studies suffer from some certain limitation. First, due to data availability, only a small stream of existing literature focus on firm-level data. Among these studies, most of them examine firms in one specific sector/region/province which indicates the lack of commonality. Second, the measurements for eco-innovation and environmental performance in different studies are highly country or industry specific.

3.3 Data and empirical strategy

3.3.1 Data

For this study, we employ firm-level data for French manufacturing firms due to two reasons. First, French economy was severely affected by the oil shocks in the early 1970s. Since then, the French government started restructuring the country's energy structure in order to reduce its reliance on imported fuel supplies and to achieve energy independence. A serious of actions from the government motivate the development of nuclear programs for electricity generation where CO_2 emissions are much smaller for electricity produced by nuclear and hydropower than that of coal, oil, or natural gas. Figure 3.2 illustrates the dominant position of nuclear power where the fraction of nuclear power generated electricity to the total electricity produced in France was 72% in 2017. Also CO_2 emissions per capita in France have declined from 9.3 tonnes to 7.7 tonnes between 2000 and 2017. Although France contributed to about 0.91% of the world's total CO_2 emissions in 2017, its CO_2 emissions are the lowest among the major Western European countries (Eurostat, 2019). Secondly, as the third largest economy in the EU, France assigns a significant amount of resources to R&D activities every year. France devotes approximately 4,8643 millions euros in R&D activities in 2015 which ranked second in terms of investment in the EU. These R&D expenditures account for approximately 2.23% of total French GDP which is ranked seventh in the EU (Bank, 2017).

[Figure 3.2 about here]

For our empirical analysis, we construct an unbalanced panel data set which comprises four different data sources in order to investigate the effect of eco-innovation on environmental performance. First, we use the EACEI (Annual survey on industrial energy consumption) survey that is a survey of manufacturing plants and asks for information on quantities and values of energy consumed by energy type. More specifically, different uses of each type of energy source are included. This survey also includes other non energy related variables such as employment, geographical location. Different energy sources include electricity (bought, self-produced and resold), steam, natural gas, other types of gas available on the network, coal, lignite, coke, butane, propane, heavy fuel oil, heating oil, other petroleum products, the black liquor (a byproduct from the chemical decomposition wood for making paper pulp), wood and its by-products, special renewable fuels, special non-renewable fuels. And different uses of electricity include driving force, thermal use, other uses (including electrolysis). For other types of energy, different uses include manufacturing, electricity production, raw materials, heating and other purposes. In our sample period (2005-2012), certain sectors such as Manufacture of food products, beverages and tobacco products were not surveyed, thus all plants from these sectors are excluded from our analysis. Since

2007 onward, other non-manufacturing industrial sectors such as Material recovery were included in the survey but are dropped from our analysis for consistency. The data has around 12,000 plants every year and includes all manufacturing plants employing over 20 employees in the most energy consuming sectors (including Manufacture of bricks, tiles and construction products, in baked clay, Manufacture of cement and Manufacture of lime and plaster); all plants with more than ten employees in manufacturing of industrial gases sector; all plants with more than 250 employees on the 31st of December of that year; a sample of plants with employment between 20 and 249 employees in sectors that are not energy intensive. The level of the survey is at plant level rather than firm level given that energy consuming materials, electricity and gas meters and fuel tanks are held at that level. In our analysis, we aggregate the plant-level data to the firm level by subtracting the first 9 digit firm-level code (SIREN) which is the unique French business identification number from the 16 digit plant-level code (SIRET). Firms with no plant appearing in EACEI are dropped from our sample. We assume that any missing observations from EACEI are very small in comparison to reporting plants. [3]

Second, we include the annual survey of resources devoted to R&D activities (Enquete annuelle sur les moyens consacres a la R&D) collected by the French Ministry of Education and Research in our panel. This survey includes over 7,000 firms that perform R&D activities. This data set provides a detailed representation of the innovation activities carried

[3] This assumption may have an impact on our main results if a firm has several plants below the threshold that are not surveyed by EACEI and a large plant that is surveyed by EACEI, under our assumption, then this firm's total energy uses equals to a firm's largest plant's energy use. However, if the summation of the small plants' usage is not small compared to the large plant, then the firm's total energy usage is underestimated. This measurement error could lead to biased coefficient of interest.

out by French firms in terms of internal and external resources, the number of employees working for the R&D department, public funds received, the number of patents and indicators of product and process innovations.

Note that all firms in this data set are innovators. Due to the sampling structure, this is a census survey for those firms which invest more than 350,000 in innovation whereas firms that only invest relatively small amounts in R&D are randomly selected. Thus one problem with this data is missing values and firms with long year gaps between observations. To obtain a consistent panel, we drop all firms with more than six years gaps between data points from our sample. After removing those firms, we construct a panel data set using extrapolation techniques to fill in missing observations.

Third, we include financial information on manufacturing firms using two data sets. The first is the Unified and Comprehensive File of SUSE (FICUS) database that is based on an annual fiscal census of firms called the Unified Corporate Statistics System (SUSE) which is conducted by the French Ministry for the Economy and Finance and is at the firm level. SUSE covers all firms that are under the industrial and commercial benefit (BIC) tax system or under the non-commercial benefit (BNC) tax system, and this means SUSE comprises all firms that send their tax return to the French Ministry for the Economy and Finance. It gives an unbalanced panel of over 3 million manufacturing firms for a period of 14 years between 1994 and 2007. Three kinds of variables are available. First, there is firm information such as primary industry classification at the 4 digit NACE level, employment and date of creation. Second, there are income statement variables such as total turnover, total labour cost and total gross earnings. Third, there are balance sheet variables such as debt and stock of capital. The second data set for financial data is the Approached File of ESANE Results (FARE). ESANE is the Annual Business Statistics Production and the FARE data replaced FICUS after 2008. Hence, to obtain fiscal data for 2008 on wards, we use the FARE file that gives an unbalanced panel of firms for the period 2008 to 2012.

After merging the four different data sets, we remove inconsistent observations and coding errors from our sample, including incomplete data, negative values for R&D expenditure and other contradictory information. In addition, we drop all firms with less than 10 full-time equivalence employees. All monetary variables are represented in thousands of Euros and have been deflated using French Producer Price Index at the sector level with 2010 as a baseline (INSEE, 2017). Our final sample is an unbalanced panel comprised of almost 7,000 observations for about 1,800 French manufacturing firms over 8 years. We also distinguish between pollution intensive and non-pollution intensive sectors. Following Shimamoto (2017), we categorize the five pollution intensive sectors as (1) Manufacture of pulp, paper and paper products, (2) Manufacture of chemicals, chemical products and man-made fibres, (3) Manufacture of coke, refined petroleum products and nuclear fuel, (4) Manufacture of other non-metallic mineral products and (5) Manufacture of basic metals and fabricated metal products. Although analysing the full-sample can generalize to the population of French manufacturing firms, by investigating two sub-samples of firms, we can focus on more homogeneous sets of firms with specific characteristics. Following OECD

(2019) definition on fossil fuels, we define fossil fuels as resources derived from the remains of ancient plant and animal life, including coal, oil and natural gas.

3.3.2 Data Description

After aggregating the energy uses data from EACEI, we are able to generate the total energy consumption in the unit of tonnes of oil equivalent at the firm level. Then we transform the total energy consumption into CO_2 emissions in the unit of tonnes by multiplying the energy conversion index from the International Energy Agency (IEA) (International Energy Agency, 2019). We firstly measure environmental performance using firm-level CO_2 emissions intensity which is defined as the CO_2 emissions in the unit of tonnes divided by total output. Secondly, we apply the fossil fuel intensity as an additional indicator for environmental performance. We generate the total fossil fuel consumption by summing up different types of fossil fuels (including coal, oil and natural gas). [4] Then we define the fossil fuels intensity as dividing fossil fuel consumption in the unit of tonnes of oil equivalent by total turnover.

Regarding eco-innovation, we use environmental R&D expenditures as a proxy. In our R&D data, the distribution of internal R&D is provided and one of the categories is the percentage of R&D expenditures dedicated to the protection of the environment. Therefore the degree of investment in eco-innovation is calculated by multiplying the share of

[4] Following OECD (2019) definition on fossil fuels, we include natural gas, other types of gas available on the network, coal, lignite, coke, butane, propane, heavy fuel oil, heating oil, other petroleum products and the black liquor as fossil fuels. Wood is recognized as a renewable source, thus it's not included.

environmental R&D expenditures with the amount of total internal R&D expenditures. The degree of eco-innovation captures the extent of a firm's internal R&D investment in environmental innovation. Table 3.2 presents descriptive statistics of the different variables used in our econometric analysis. The average size of the firm is approximately 618 full-time equivalent employees which indicates our sample focus on relatively large firms. [5]

[Table 3.2 about here]

In Table 3.3 we distinguish firms between polluter and non-polluters. In our sample, 538 French manufacturing firms are classified as pollution intensive representing approximately 28% of the sample. From Table 3.3, we observe that polluters have a higher CO_2 intensity as well as fossil fuel intensity as expected. Meanwhile, polluters appear to be less productive and pay more wages to employees. Polluters are smaller in term of size whereas they invest more in eco-innovation. Regarding R&D capabilities, even though polluters make much less R&D investment, it seems that they outsource more R&D activities to external partners comparing with non-polluters.

[Table 3.3 about here]

Figure 3.3 illustrates that the annual average energy mix of the French manufacturing

[5] We follow Levinsohn and Petrin (2003) approach to calculate total factor productivity (TFP). This approach is based on using intermediate inputs (investment and materials) to proxy for the unobserved productivity. We use total investment in tangible and intangible assets as a proxy for the intermediate input. We further use logarithm of the value added of firm as proxy for output, the log of capital and the log of labour in the estimation of the firm's productivity.

firms, and these values appear quite stable throughout the period of 2005 to 2012. French manufacturing firms substantially rely on electricity (mostly from nuclear, e.g. 72 percent in 2017), which accounts for approximately 55 percent of total energy consumption and has modestly increased by approximately 5 percent over the period considered. The second most important energy input is natural gas, which accounts for approximately 35 percent of total energy consumption. Finally, other energy sources (heavy oil, oil, steam, coke, other gas, coke-petrol, and lignite) only represent a very small share of the energy input for the typical firms.

[Figure 3.3 about here]

In Figure 3.4 we plot the annual average CO_2 intensity over time from 2005 to 2012 and show a stable trend of reduction of emissions during this period. The average CO_2 intensity decreases for about 25%. Meanwhile, in Figure 3.5, we present the annual environmental R&D expenditures. The significant increase of the average value of eco-innovation shows that French firms are investing increasing resources to internal environmental R&D over this time period.

[Figure 3.4 about here]

[Figure 3.5 about here]

Figure 3.6 presents the distribution of CO_2 intensity for firms across different sectors. We can observe considerable sectoral variation in the CO_2 intensity and confirm the existence of sectoral heterogeneity. In particular, we observe that paper and pulp sector and non-metallic mineral sector have the highest CO_2 intensity across all manufacturing industries.

[Figure 3.6 about here]

3.3.3 Empirical strategy

In this chapter, We aim to evaluate the effectiveness of eco-innovation in improving French manufacturing firms environmental performance. First, we use the system generalized method of moments estimation (GMM) method to investigate the dynamic impact of eco-innovation on CO_2 intensity in France. For another, we discuss whether, or not, investing in eco-innovation can reduce CO_2 intensity, by applying the propensity score matching combined with difference in difference (PSM-DiD) estimation method.

3.3.3.1 System GMM estimation

The use of pooled least square and fixed effect method could suffer from potential bias including unobserved heterogeneity, omitted variable bias and measurement error. Regressors may not be strictly exogenous which would cause endogeneity concerns (Biresselioglu et al., 2016). To overcome the bias, we implement the system GMM approach to examine the dynamic variation of environmental performance for French manufacturing firms during the time period from 2005 to 2012. System GMM approach provides efficient and consistent parameter estimates. In particular, system GMM allows for more instruments comparing with first difference GMM (Blundell and Bond, 1998) and moreover, system GMM is more efficient due to the existence of heteroskedasticity (Arellano and Bond, 1991). We apply a dynamic model by including lag of the CO_2 intensity as an additional regressor and we instrument potential endogenous variables with their three periods lagged value. However, no significant second-order autocorrelation in the residual series assumption needs to be tested, because such an autocorrelation will make the lags of endogenous variables inappropriate instruments. Besides, the instrument validity is directly tested by the Sargan and Hansen tests (Hansen, 1982; Sargan, 1958). In this chapter, the system GMM model, which examines the impact of eco-innovation on carbon emissions intensity, is as follow:

$$\begin{aligned} Co2\_intensity_{i,t} = &\beta_1(Co2\_intensity_{i,t-1}) + \beta_2(EnvR\&D\_intensity_{i,t-1}) \\ &+ \beta_3(F_{i,t-1}) + \beta_4(T_{i,t-1}) + \mu_t + \gamma_j + \sigma_l + \epsilon_{i,t} \end{aligned} \tag{3.1}$$

where Co2_intensity is the CO_2 intensity of firm i in year t and EnvR&D_intensity is the eco-innovation intensity of firm i in year $t-1$. In the first set of variables F, we include those control variables including firm age, firm size, average wage, ownership of firm, TFP, and leverage. Then in the second set of variables T, we include a series of variables to capture firms' technological capabilities that include R&D intensity and external cooperation R&D dummy. In addition, year μ_t, sector fix effects at the NACE rev.1 two digit level γ_j and regional fix effect σ_l are included in all specifications to control for time invariant factors common to firms across different regions and sectors respectively while year dummies to account for business cycle effects. Furthermore, given that investment in eco-innovation usually takes a long period to complete and to generate returns (Brunnermeier and Cohen, 2003), we impose a lag structure to control for the delayed effect.

Similarly, the system GMM model examining the impact of eco-innovation on fossil fuel intensity is as follow:

$$\begin{aligned} Fossilfuel\_intensity_{i,t} =& \beta_1(Fossilfuel\_intensity_{i,t-1}) + \beta_2(EnvR\&D\_intensity_{i,t-1}) \\ &+ \beta_3(F_{i,t-1}) + \beta_4(T_{i,t-1}) + \mu_t + \gamma_j + \sigma_l + \epsilon_{i,t} \end{aligned} \tag{3.2}$$

where Fossilfuel_intensity is the fossil fuel intensity of firm i in year t. We include the same set of control variables as for CO_2 intensity.

3.3.3.2 PSM-DiD estimation

Furthermore, we investigate the effect of starting to eco-innovate by comparing a firm's environmental performance, several years after starting to innovate to what their hypothetical performance would have been at the same time had they never begun to invest in eco-innovation. The estimation comparing reality with hypothetical performance is not straightforward. The reduction of CO_2 emissions is also likely affected by other endogenous factors as discussed in previous section. For instant, a potential source of bias comes from the endogenously determined CO_2 emissions allowance prices by EU Emissions Trading Scheme (ETS) (Lise et al., 2010). Moreover, unlike natural experiment, the counterfactual of not being treated for an observation which instead has invested in eco-innovation is unobservable, which cause difficulties in assessing the real effect of eco-innovation while controlling for other relevant factors.

Thus, Our empirical strategy is to employ propensity score matching (PSM) and difference-in-difference (DiD) approach to identify this causal link between eco-innovation and environmental performance. A concern of applying the simple PSM approach is that it does not control for any unobserved firm characteristics that may influence the outcome (Caliendo and Kopeinig, 2008). Thus, depend on observable differences between eco-innovators and non eco-innovators, we construct a control group to control for selection on observable and unobservable time-invariant heterogeneity. After matching, we apply a DiD approach to estimate the treatment effect of eco-innovation on CO_2 emissions intensity. We are able to justify whether there is any variation in the environmental performance before and after they start investing in eco-innovation and also to compare the results to a control group of comparable firms that remain investing no resources to eco-innovation. Hence, a combined PSM-DiD method enhances the reliability of the estimation results.

In this study, our treatment ($newEI$) is the decision of a firm to devote to eco-innovation which equals to 1 if a firm invests positive environmental R&D for the first time at some point within our sample period. Meanwhile, the outcome is the subsequent environmental performance of a firm measured by this firm's CO_2 emissions intensity and fossil fuel intensity. In order to identify whether there are differences in firms' emission intensities or fossil fuel intensity following the decision to invest in eco-innovation, we only focus on new eco-innovators. To identify our treatment, we drop all firms which invest in eco-innovation consistently across our sample period. These firms do not switch at all and do continuous eco-innovation. Then, we re-scale the time period that we denote $t = 0$ when a firm invests in eco-innovation for the first time or as the median year for non eco-innovators. Based on the re-scaled t, we drop all subsequent observations of the same firm to avoid duplicate matches.

To start the matching process, we denote y_{it} as firm i's environmental performance (CO_2 emissions intensity or fossil fuel intensity) in time period t and $y_{i(t+n)}$ as the environmental performance n period later ($n \geq 0$). Then the effect of eco-innovation on environmental performance of firm i at $t + n$ is as follow:

$$y^1_{i(t+n)} - y^0_{i(t+n)} \tag{3.3}$$

We examine the average treatment effect on the treated (ATT), as the difference in firms' environmental performances (CO_2 emissions intensity) between those which newly implement the treatment (devote to eco-innovation) and those which remain eco-innovation inactive, by computing:

$$ATT = E[y^1_{i(t+n)} - y^0_{i(t+n)} \mid newEI_{it} = 1] = E[y^1_{i(t+n)} \mid newEI_{it} = 1] - E[y^0_{i(t+n)} \mid newEI_{it} = 1] \tag{3.4}$$

where $newEI$ equals to one if firm i starts devoting resources to eco-innovation at time t and zero otherwise. For 3.4, although we are able estimate $E[y^1_{i(t+s)} \mid newEI_{it} = 1]$, we are not able to estimate the counterfactual for the same firm $E[y^0_{i(t+s)} \mid newEI_{it} = 1]$, since we do not observe the outcome directly.

Thus, following previous literature (Rosenbaum and Rubin, 1983; Heckman et al., 1997; Dehejia and Wahba, 2002), we construct a valid control group of observations. In our estimation strategy, each new eco-innovator is matched with a comparable observation which is another firm with similar characteristics but has never devoted any resources to eco-innovation. We also make an assumption that matched firms are similar in terms of observable characteristics as well as unobservable characteristics. The expression is as follow:

$$E[y^0_{i(t+n)} \mid newEI_{it} = 1, C] = E[y^0_{i(t+n)} \mid newEI_{it} = 0, C] \tag{3.5}$$

where C represent a set of covariates of firm characteristics. Thus we are able to apply the method above and re-write Equation 3.4 as follow:

$$ATT = E[y^1_{i(t+n)} \mid newEI_{it} = 1, C] - E[y^0_{i(t+n)} \mid newEI_{it} = 0, C] \tag{3.6}$$

However, it is unlikely to find identical values for all covariates in C. Rosenbaum and Rubin (1983) suggest that the control group can be constructed condition on the conditional probability of receiving a treatment given pre-treatment characteristics:

$$P(C) = Pr(newEI_{it} = 1 \mid C) = E(newEI_{it} \mid C] \tag{3.7}$$

where P is the propensity of firm i to start eco-innovation at time t. Thus due to the binary nature of the treatment (newEI), we estimate the probability of the treatment (newEI) at time t using Probit estimation given by:

$$Pr(newEI_{i,t} = \beta_1(C_{i,t-1}) + \mu_j + \gamma_k + \sigma_l + \epsilon_{i,t} \tag{3.8}$$

where C includes covariates of firm characteristics for firm i at year $t-1$. C comprises firm age (Log_age), firm size (Log_size), average wage ($Log\_avewage$), ownership of firm ($French\_firm$ and $Foreign\_firm$), TFP (TFP), leverage ($Leverage$), R&D expenditure ($Log\_R\&D$) and external cooperation R&D dummy ($ExtR\&D\_d$). Table 3.1 provides detail definitions of covariates that we included in the estimation.

[Table 3.1 about here]

In addition, we take into account invariant characteristics through using a set of year dummies (μ_t) to control for business cycle effects common to all business. Also we include two digit NACE rev.1 sector dummies (γ_j) to control for time invariant factors common to firms across different sectors. Furthermore, we control for the regional differences by introducing regional dummy variables (σ_l) which cover 25 administrative regions.[6]

We lag all time-variate explanatory variables by one year to control for reverse causality. In addition, we include the pre-treatment growth of outcome variable in the estimation. For instant, Firms that start to invest in eco-innovation may already have different CO_2 emissions intensities comparing to firms that never devote to eco-innovation. Historical CO_2 emissions may affect current CO_2 emissions, by taking pre-treatment growth, we are able to avoid potential bias. For the estimation on the impact of eco-innovation on the fossil fuel intensity, we also lag all time-variate explanatory variables by one year, but we replace the pre-treatment growth of CO_2 emissions intensity by the pre-treatment change of the share of fossil fuel in total energy consumption to avoid potential influence of historical energy mix.

Table 3.4 presents the results of the Probit estimations for estimating the propensity scores for CO_2 emissions intensity.[7] Regarding Table 3.4, results show a positive and significant effect of TFP on eco-innovation which indicates that more productive firms have higher probability of being new eco-innovators. We also find that subcontracting R&D activities to external partners would increase the probability of being an eco-innovator. For pollu-

[6] 25 administrative regions comprise 22 regions in Metropolitan France and 3 overseas regions. Since in 2014, the French parliament passed a law reducing the number of metropolitan regions from 22 to 13 effective 1 January 2016, we adopt the previous legal concept of regions.

[7] We include firm characteristics for firm i at year $t-1$. C including firm age (Log_age), firm size (Log_size), average wage ($Log\_avewage$), ownership of firm ($French\_firm$ and $Foreign\_firm$), TFP (TFP), leverage ($Leverage$), R&D expenditure ($Log\_R\&D$) and external cooperation R&D dummy ($ExtR\&D\_d$).

tion intensive firms in column (2), similar results are noted comparing with column (1). Additionally for non pollution intensive firms, paying higher wage to employees would also increase the probability of being an eco-innovator.

[Table 3.4 about here]

After estimating the propensity scores (predicted probabilities) from the Probit estimation, we start the matching. The matching is executed within each two digit NACE rev.1 sector and for each year to avoid matching across the entire sample (Elliott et al., 2016). Firms in different sectors may have different technological levels, thus the propensity to start investing in eco-innovation would be different subsequently between different sectors. This approach generates more homogeneous control groups within narrowly defined industries in the same year.

A number of matching algorithms have been developed in the literature, such as kernel matching, radius matching, caliper matching and nearest neighbour matching (Stuart, 2010). Austin (2014) suggests that different matching algorithms are differentiated in terms of how the neighborhood of control firms is built around the treated observations and different matching algorithms make a trade-off between bias and variance. In this study, we apply kernel matching and radius matching. Kernel matching gives each treated firm a weight of one. A weighted composite of control observations is used to create a match for each treated firm, where control firms are weighted by their distance in propensity score from treated firms within a range of the propensity scores. Garrido et al. (2014)

suggest that kernel matching maximizes precision by retaining as many observations without worsening bias by giving higher weight to better matches. We also impose a common support condition. When applying kernel matching, we need to choose the range of the propensity scores (bandwidth parameter). High bandwidth values lead to a smoother estimated density function, which means a better fit and a decreasing variance between the estimated and the true underlying density function. However, a high bandwidth would potentially smooth away underlying features which may cause a biased estimate (Caliendo and Kopeinig, 2008). Since Austin (2011) suggests that a bandwidth of 0.02 tends to performance better in estimating treatment effect, thus we choose the bandwidth of 0.02 for Kernel matching. Furthermore, we apply radius matching which is a variant of caliper matching Dehejia and Wahba (2002). The difference is to use all of the comparison units within the caliper instead of using the nearest neighbor within each caliper only. A benefit of this matching technique is that it uses as many comparison members as are available within the caliper and therefore allows for usage of extra units when good matches are available.

After estimating the propensity scores, we then perform the balancing test to examine the quality of the matching across treated and control groups. We split the sample into k blocks of the propensity scores and test within each block whether the mean propensity score is equivalent in the treated and control groups (Dehejia and Wahba, 2002; Garrido et al., 2014). If the balancing test fails, we split the interval into more blocks and test again. We continue this process until equality holds for every interval. After the propensity scores are balanced within blocks across the treated and control groups, we check for the balance of each observed covariates within blocks of the propensity scores. If the balancing test fails, we modify covariates in the estimation until equality is achieved.

After matching, we employ DiD estimation to estimate the differences of the CO_2 emissions intensity for eco-innovative firms in the year they started investing in eco-innovation and the subsequent three years with respect to the pre-treatment level and to compare it with the corresponding changes for persistent non eco-innovators. Since DiD estimator removes the effects of common shocks and time invariate unobservables, combining PSM and DiD allows for the selection on unobservable determinants based on similar characteristics of different firm and time specific components of the error term. Thus, Our PSM-DiD estimator is as follow:

$$
\begin{aligned}
ATT^{PSM-DiD} &= \frac{1}{s_{treated}} \sum_{newEI=1} [(y_{treated,post} - y_{treated,pre}) - \sum_{newEI=0} w_{ij}(y_{control,post} - y_{control,pre})] \\
&= \frac{1}{s_j} \sum_{j \in treated} [(y_{j,t+n} - y_{j,t-1}) - \sum_{k \in control} w_{jk}(y_{k,t+n} - y_{k,t-1})]
\end{aligned}
\tag{3.9}
$$

where s_j is the number of observations in the treated group on the common support. t is the year when a firm first devotes to eco-innovation, so $t+n$ is n periods after the treatment occurs ($n \geq 0$). w_{jk} is the weight placed on the matched control firm k when constructing the counterfactual estimation for treated firm j. Due to the time period is between 2005 and 2012, we compare the change in the CO_2 intensity for three years after the initials investment in eco-innovation ($n \in 1, 2, 3$).

The application of PSM-DID approach improves the quality of our empirical analysis. In particular, matching based on a number of observable characteristics allow us to compare closely related observations, characterized by similar firm-level factors and to tackle the endogeneity issue (Blundell and Dias, 2009). Furthermore, this technique remove the effects of common shocks and provide a robust estimation of the causal link between eco-innovation and CO_2 intensity at the firm-level for French manufacturing firms.

3.4 Empirical results

We start by estimating the dynamic effect of eco-innovation on CO_2 emissions intensity for French manufacturing firms during 2005–2012 in Table 3.5. Specification (1)–(3) imply estimation results on all firms, pollution intensive firms and non-pollution intensive firms. To determine the goodness of fit of the system GMM estimation, we report the second-order autocorrelation for the residual series assumption and the Hansen tests of over-identifying restrictions. We cannot reject the null hypothesis of the second-order autocorrelation for the residual series at 10% level and meanwhile, the Hansen tests show insignificant P-value at the 10% level, suggesting that the identification of instrument variables are just identified. Tests results justify the validity of the model.

[Table 3.5 about here]

First, for all firms in Specification (1), results show a strong degree of persistence in CO_2 emissions intensity as expected. Meanwhile, focusing on our key variable, we notice a positive but insignificant coefficient for eco-innovation. This suggests that the effect of eco-innovation on CO_2 intensity is not recognized in our sample. Regarding technological capabilities, we find that R&D intensity is negative but insignificant. However, we observe a negative and significant effect of firm size on CO_2 intensity suggesting that larger firms are more environmental efficient comparing with small firms. Also a negative and significant effect of firm age is observed which is suggesting that more mature firms are less emitting due to the greater capability of reducing their CO_2 intensity. And this capability can be either organizational or technological.

In Specification (2) and (3), we make a distinction between pollution intensive firms and non pollution intensive firms following Shimamoto (2017). Focusing on our key variable, we find consistent results that eco-innovation remains insignificant in reducing CO_2 intensity across both specifications. Specifically in Specification (2), we find that pollution intensive firms show similar characteristics comparing with our baseline estimation in Specification (1) that results show high persistence in CO_2 intensity. However, looking at specification (3), we find a negative and significant coefficient for TFP which indicates that for non-pollution intensive firms, more productive firms are more environmental efficient. Results also suggest that devoting more resources to R&D is likely to lower CO_2 intensity. But subcontracting R&D to external partners, by contrast, would increase firm's CO_2 intensity.

Second, we report the results on examining the effects of starting to eco-innovate by comparing a firm's CO_2 intensity, several years after starting to innovate to what their hypothetical performance would have been at the same time had they never begun to devote to eco-innovation. In our sample, we find 395 new eco-innovators and 1270 firms that have never invested in eco-innovation during 2005-2012. Before interpreting the treatments effect, we implement several balancing tests which provide useful information on whether plausible counterfactuals have been created to justify the overall performance of the matching process. Firstly, based on the estimated propensity scores, we compare differences in the means of the observable characteristics before and after the matching for firms from treated and control groups. Differences between the treated and the control groups are expected before matching, but should reduce significantly after matching has taken place. Secondly, we check the standardized difference (SD) for variables between treated and control groups. Low standardized difference suggests variables being used in the PSM are balanced between treated and control groups. Different from t test, SD is not affected by sample size.

In Table 3.6 and Table 3.7 we present the balancing tests results on Kernel matching for eco-innovation on firm's CO_2 intensity for our main specification. Table 3.6 comprises the comparison of individual covariates considered in the Kernel matching process between treated and control groups before and after matching. We find the presence of differences in some covariates between treated and control groups before matching, however bias are decreased substantially in the matched samples. The t-test results confirm our findings. Table 3.7 provides information on overall measures of covariate imbalance before and after matching. Comparing the pseudo-R^2s before and after matching, there are no systematic differences in the distribution of covariates between treated and control groups after matching, thus the pseudo-R^2 is relatively low. Also, the likelihood ratio test on the joint significance of all variables in the matching process show rejection before matching but not after matching. Overall, tests results suggest a well balance after matching. Thus, we confirm that there are no systematic differences in observable characteristics between the treated and the control groups. Hence the matching quality is satisfactory.

[Table 3.6 about here]

[Table 3.7 about here]

Now we start evaluating the effectiveness of eco-innovation on firm's CO_2 emissions intensity. PSM-DID results for main specification using two different matching techniques, namely Kernel matching with the bandwidth of 0.02 and radius matching with a caliper of 0.02 are presented in Table 3.8 respectively. Common support and replacement are considered during the matching. The results for Kernel matching are shown in the upper part of Table 3.8. ATTs show a positive treatment effect, but this effect remains statistically insignificant for up to three years. The estimates indicate that there's no significant reduction in the CO_2 emissions intensity for new eco-innovators in the year that they start to invest in eco-innovation, comparing with comparable firms that did not start to invest. Furthermore, after the one, two and three years when the initial decision of investing in eco-innovation was made, the CO_2 emissions intensity is still not significantly affected by this decision.

[Table 3.8 about here]

For Kernel matching, we chose the bandwidth of 0.02 and radius matching with a caliper of 0.02. According to Austin (2011), using caliper widths equal to 0.2 of the standard deviation of the estimated propensity score and caliper widths equal to 0.02 or 0.03 tend to have better performance for estimating treatment effects. Thus we further apply Kernel matching with a bandwidth of 0.2 of the standard deviation of the estimated propensity score and radius matching with a caliper of 0.2 of standard deviation of the estimated propensity score in Table 3.9 and the results are fairly consistent with Table 3.8

[Table 3.9 about here]

In Table 3.10 we make a distinction between those firms categorized as pollution intensive firms and non-pollution intensive firms following Shimamoto (2017). The upper part of Table 3.10 shows that for pollution intensive firms that start investing in eco-innovation, their CO_2 emissions intensities are not significantly reduced in the year when they become eco-innovators. Similar results are presented in the lower part of Table 3.10 for non-pollution intensive firms.

Thus, we find consistent results across two approaches suggesting there's no significant effect of eco-innovation on CO_2 emissions. One possible explanation could be that eco-innovation focuses more on product innovation which has a smaller impact on emission reduction than process innovation. Another possible explanation could be due to the specific requirements from environmental regulation. If a new environmental standard is implemented, eco-innovation may not result in cleaner production, but rather enable the firm to meet the target at a lower cost. Furthermore, since French manufacturing firms rely substantially on the consumption of electricity and the electricity consumed are mostly from nuclear power (e.g. 72 percent in 2017), CO_2 emissions intensity is relatively stable during of sample period. This may potentially weaken the results of the impact of eco-innovation on CO_2 emissions intensity.

[Table 3.10 about here]

Given the unique energy structure in France during our sample period and the insignificant effect of eco-innovation on CO_2 emissions intensity, the next stage is to investigate whether eco-innovation could change a firm's energy strategy by reducing the fossil fuel intensity. We follow the same procedure as explained in the previous section by implementing system GMM and PSM-DiD estimations. Table 3.11 presents the results of the system GMM estimation on the dynamic effect of eco-innovation on the fuel intensity. Table 3.14 presents the main results of the PSM-DiD estimation on the effects of starting to eco-innovate by comparing a firm's fossil fuel intensity, several years after starting to innovate with control group. To evaluate the overall goodness of fit of the GMM model, wee find that all of our specifications passed the second-order autocorrelation for the residual series assumption and the Hansen tests of over-identifying restrictions, suggesting the validity of the results.

In Table 3.11 Specification (1) for all firms, we can only observe the existence of high persistence fossil fuel intensity. More specifically, a positive but insignificant coefficient for eco-innovation is noted which indicates the eco-innovation does not significantly affect firm's fossil fuel intensity. And this insignificant effect of eco-innovation is relatively consistent across all specifications when we distinguish between pollution intensive firms and non pollution intensive firms in specification (2) and specification (3) respectively. For specification (2), pollution intensive firms show very similar results comparing with specification (1). If we focus on non-pollution intensive firms in specification (3), R&D intensity seems to be a significant factor in reducing the usage of fossil fuel. However, if a firm subcontracted R&D to external partners in the previous year, its fossil fuel intensity would increase by 0.16%. Results show a negative and insignificant effect of TFP on the fossil fuel intensity whereas larger and more mature firms appear to have lower fossil fuel intensity.

[Table 3.11 about here]

Secondly, we examine the effects of starting to eco-innovate on fossil fuel intensity by comparing a firm's fossil fuel intensity with control group. Again, we implement several balancing tests before interpreting our PSM-DiD results and results are presented in Table 3.12 and Table 3.13. Table 3.12 illustrates that the matching process substantially reduces the bias for most of the covariates, and the variance ratios between treated over non-treated indicate a good balance for most of the covariates. From Table 3.13 on the overall performance of the matching procedure, the SD of the matched sample is significantly reduced comparing with the unmatched sample. It reflects that the systematic difference between new eco-innovators and matched non eco-innovators is reduced. The insignificant P-values of the LR test indicates that no significant differences between the new eco-innovators and the matched non eco-innovators after applying the matching. Overall, results from balancing tests suggest that there are no systematic differences in the observable characteristics between treated and control groups. Thus we are able to justify that there are no specific concern for the quality of the matching.

[Table 3.12 about here]

[Table 3.13 about here]

Now we start interpreting the results presented in Table 3.14. Kernel matching technique provides positive treatment effects, but not statistically different from 0 at the 10% level for up to three years afterward. ATTs indicate that the fossil fuel intensity is not significantly influenced by the decision to start investing in eco-innovation for new eco-innovators in the year that they start to invest in eco-innovation. Nevertheless, in the first, second and third year after the initial decision of investing in eco-innovation was made, the fossil fuel energy consumption is still not significantly affected by this decision. In the lower part of Table 3.14, following radius matching technique, we notice larger ATTs with same direction. However, all ATTs are still statistically insignificant.

[Table 3.14 about here]

Overall, Our results are consistent across all specifications, confirming the robustness of our results in terms of the methodologies applied and of the validity of findings. In general, our findings do not find evidence that there is a significant relationship between eco-innovation and environmental performance. Recall that eco-innovation is related to the adoption of new or modified processes, techniques, systems and products to avoid or reduce environmental damage (Kemp, 2010). Hence, the implementations of eco-innovation is crucial in reducing emissions and wastes. However, the implementations of eco-innovation requires high initial costs, while it takes a relatively long period to recover these costs, hence, the firms' incentive may be relatively low in this case.

3.5 Conclusions

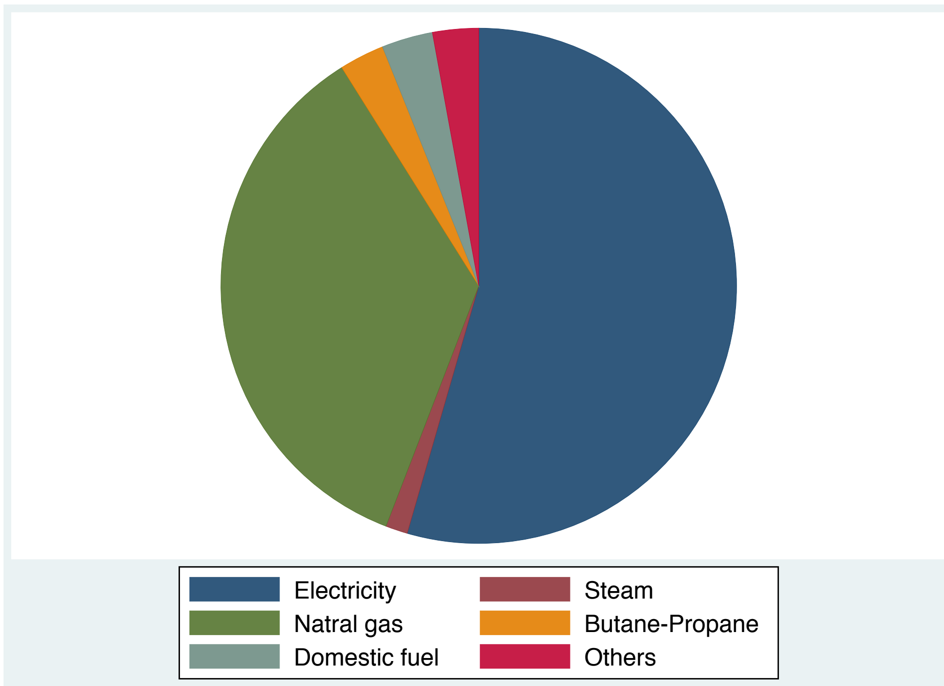
This study aims to contribute to the empirical literature examining the effect of eco-innovation on environmental performance measured by CO_2 emissions intensity and fossil fuel intensity using a firm-level panel data of French manufacturing firms that invest in R&D. In particular, we further investigate whether firms that start to invest in eco-innovation achieve a better environmental performance in the year they start to invest in eco-innovation and in the following three years comparing with the year before they start to invest. To test our arguments, we construct a panel data set containing 1,867 French firms during 2005-2012. Our Distinguish from previous studies using more aggregated data, we are able to use an identification strategy that is less sensitive to macroeconomics shocks that may be correlated with country or sector level eco-innovation and environmental performance. For our empirical results, our findings do not support the presence of a significant relationship between eco-innovation and environmental performance. More specifically, we find no evidence that eco-innovation significantly facilitates carbon emission reduction for French manufacturing firms during 2005-2012. And nevertheless, we do not find evidence that eco-innovation significantly reduce fossil fuel consumption.

The insignificant effect could be due to the special characteristics of eco-innovation. The absence of pressures to eco-innovate by key stakeholders or the lack of institutional environment, such as public policies, limits firm's incentive to invest in environmental technologies which target on reducing environmental impacts. Moreover, insufficient internal capabilities may also hinder eco-innovation, such as lack of technological capabilities to internalize external green technologies, and a low priority given to environmental issues. Nevertheless, eco-innovation may be too expensive or incompatible with the existing production process. It may fall into a scenario that firms can not invest in eco-innovations due to the costs, and costs go even higher when firms are reluctant to invest. Thus regulatory intervention is crucial in the exploitation of eco-innovation.

These results have implications for firms and policymakers regarding the effectiveness of eco-innovation in reducing carbon emissions and enhancing energy efficiency. The successful implementation of eco-innovation can help firms to meet their environmental goals and it is substantially affected by environmental regulations. However, to provide sufficient supports and incentives for firms to invest in eco-innovation, a flexible policy mix is needed. Instead of implementing stricter environmental standards which may force some firms exiting the market due to their incapabilities in dealing with new standards, using policy instruments such as public funding can be efficient. Eco-innovation is often undervalued, it's important for policymakers to support a well designed framework which provides comprehensive assessment to improve the recognition of the true value of eco-innovation for firms.

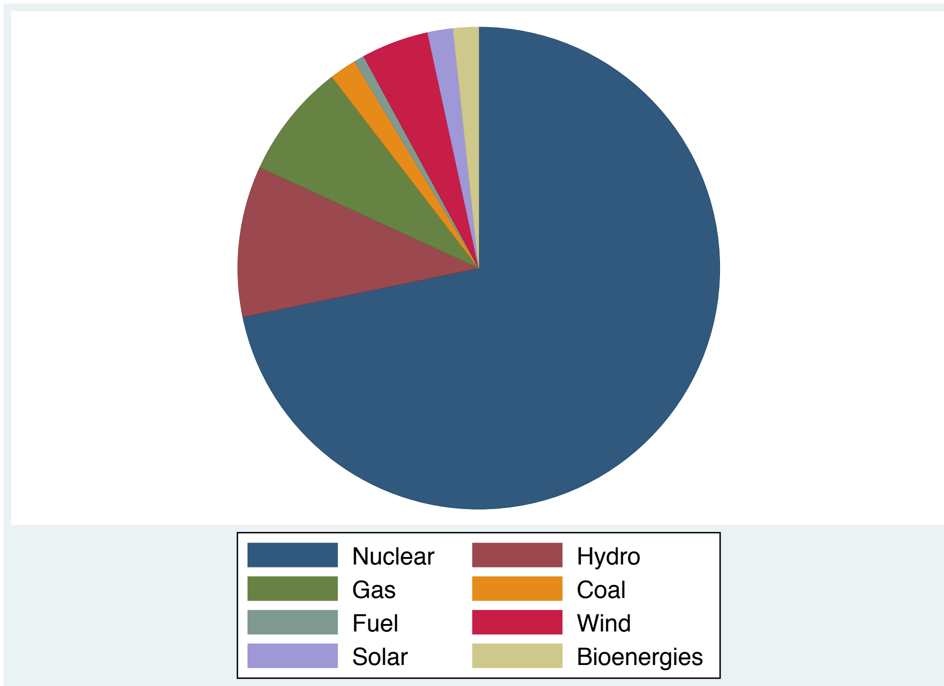
3.6 Figures and tables

Figure 3.1: Energy mix of French manufacturing firms



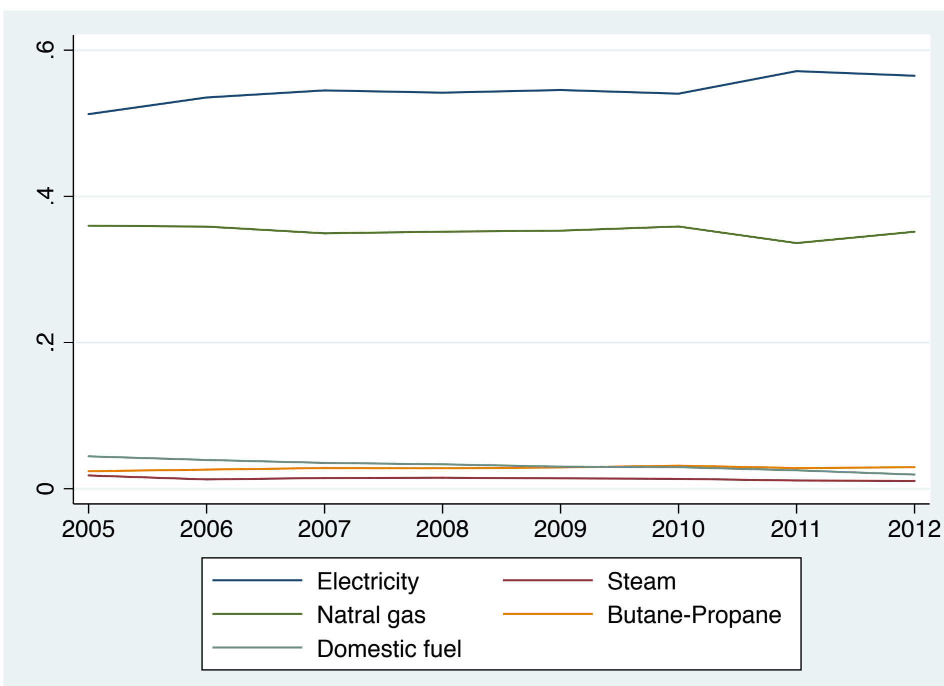
Source: elaboration based on Annual Survey on Industrial Energy Consumption database on French firms over the period 2005-2012.

Figure 3.2: Electricity generation by sources 2017



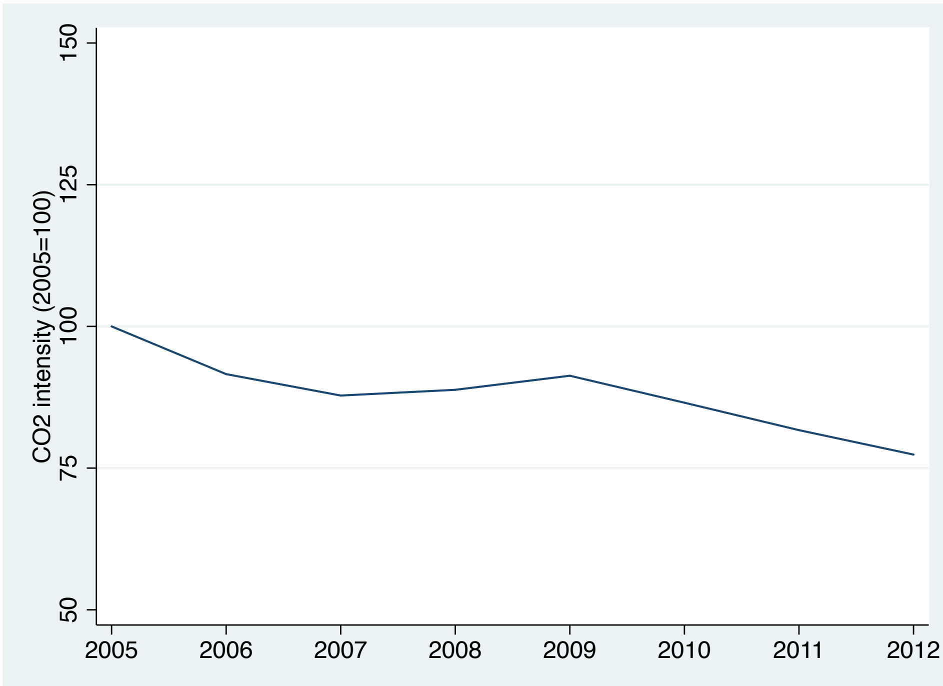
Source: elaboration based on Electricity Transmission Network database on French electricity generation 2017.

Figure 3.3: Trend of average energy mix of French manufacturing firms (2005-2012)



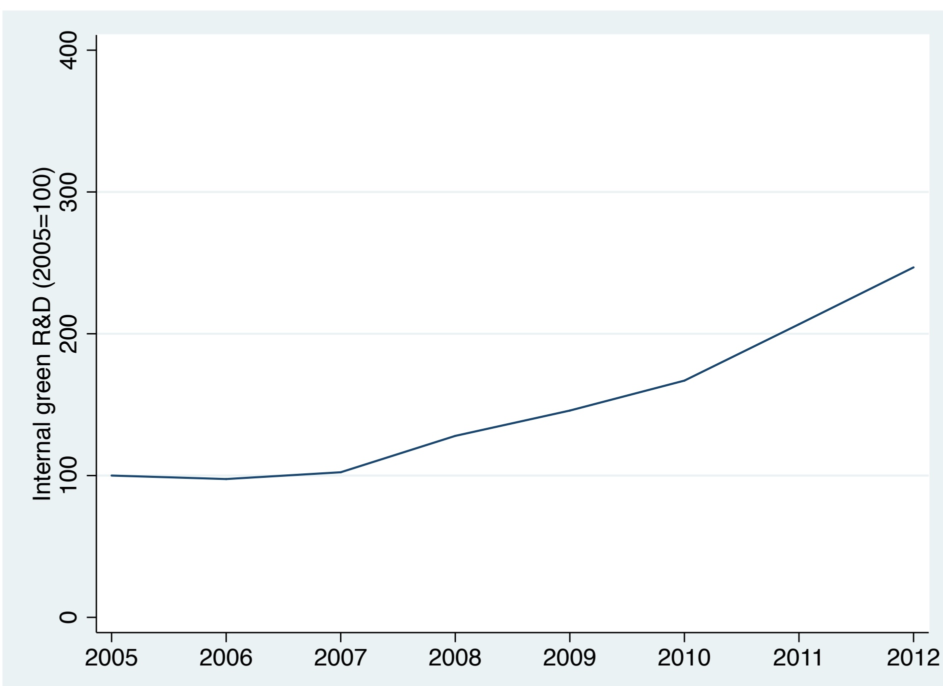
Source: elaboration based on Annual Survey on Industrial Energy Consumption database on French firms over the period 2005-2012.

Figure 3.4: Trend of average CO_2 intensity of French manufacturing firms (2005-2012)



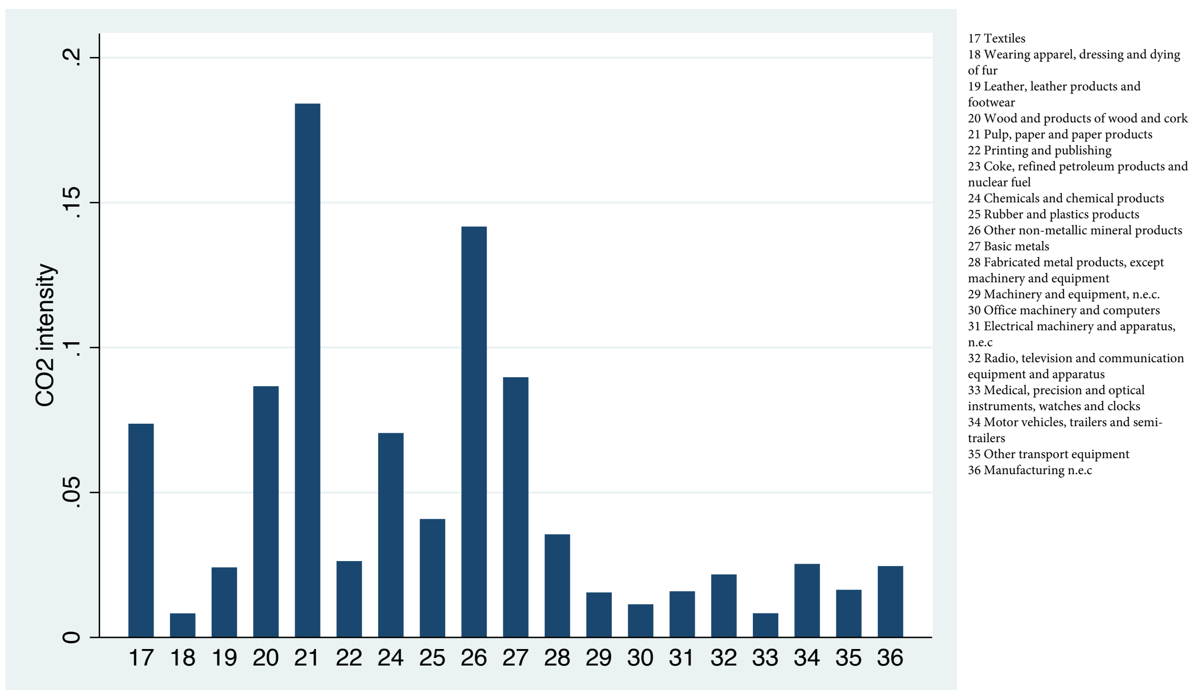
Source: elaboration based on Annual Survey on Industrial Energy Consumption database on French firms over the period 2005-2012.

Figure 3.5: Trend of average eco-innovation of French manufacturing firms



Source: elaboration based on Annual Survey of Resources Devoted to R&D Activities database on French firms over the period 2005-2012.

Figure 3.6: Average CO_2 intensity of French manufacturing firms



Source: elaboration based on Annual Survey of Resources Devoted to R&D Activities database on French firms over the period 2005-2012.

Table 3.1: Definition of variables

Variable	Description
CO_2_intensity	the CO_2 emissions divided by total output
Fossilfuel_intensity	the fossil fuel consumption divided by total output
EnvR&D_intensity	the environmental R&D expenditure divided by total output
Log_R&D	log of firm's total research and development (R&D) expenditures
ExtR&D_d	=1 if the firm is subcontracting and collaborating on R&D with external parties,
TFP	total factor productivity
Log_age	log of number of years since the firm began to operate
Log_size	log of firm's size (total number of full-time equivalent employees)
Log_avewage	log of firm's average wage (total salary expenditure divided by total number of full-time equivalent employees)
Export_intensity	the total export divided by total output
Log_export	log of firm's export value
French_group	=1 if more than 50% of share of the firm is held by a French group, 0 otherwise
Foreign_group	=1 if more than 50% of share of the firm is held by a foreign group, 0 otherwise
Leverage	ratio between total liability and shareholders' equity

Table 3.2: Summary statistics for all firms

Variable	Mean	Std.Dev	Min	Max
CO_2_intensity	0.0456	0.0857	0.0014	0.5713
Fossilfuel_intensity	0.0188	0.0571	0	0.9941
EnvR&D_intensity	0.0018	0.0085	0	0.3694
R&D (EUR th.)	10963.94	48959.18	2	1471889
R&D_intensity	0.0835	0.0808	0.0003	0.4082
ExtR&D_d	0.6083	0.4882	0	1
TFP	1.1161	0.3571	0.3419	2.3499
Age	33.7533	23.9343	2	112
Size	618.76	1236.49	12.5	24089
Avewage (EUR th.)	37.5459	9.3166	20.4895	69.9983
Export (EUR th.)	101684.5	414845.4	0	20500000
Export_intensity	0.4347	0.2856	0	0.9850
French_group	0.5236	0.4995	0	1
Foreign_group	0.4684	0.4990	0	1
Leverage	1.2996	2.2139	-7.8512	14.3536

Source: EACEI, FARE, FICUS and The Annual Survey on the Resources Devoted to R&D Activities data. Standard deviations in parentheses. Information refers to the period 2005-2012.

Table 3.3: Summary statistics of polluters and non-polluters

Variable	all firms	polluter	nonpolluters	t-test
CO_2_intensity	0.0456	0.0918	0.0260	-0.0655***
	(0.0857)	(0.1325)	(0.0416)	(0.0020)
Fossilfuel_intensity	0.0172	0.0396	0.0079	-0.0333***
	(0.0422)	(0.0679)	(0.0171)	(0.0010)
EnvR&D_intensity	0.0018	0.0022	0.0016	-0.0006***
	(0.0085)	(0.0100)	(0.0077)	(0.0002)
R&D (EUR th.)	10963.94	7047.053	12614.71	5553.34***
	(48959.18)	(22466.48)	(56423.18)	(1227.47)
R&D_intensity	0.0835	0.0845	0.0830	-0.0016
	(0.0808)	(0.0800)	(0.0811)	(0.0020)
ExtR&D_d	0.6083	0.6757	0.5799	-0.0955***
	(0.4882)	(0.4682)	(0.4936)	(0.0122)
TFP	1.1161	1.1008	1.1228	0.0222**
	(0.3571)	(0.3623)	(0.3554)	(0.0089)
Age	33.7533	35.5575	33.0022	-2.5674***
	(23.9343)	(25.6186)	(23.1396)	(0.5995)
Size	618.76	540.5885	651.88	110.41***
	(1236.49)	(856.7569)	(1363.58)	(30.9827)
Avewage (EUR th.)	37.5459	39.7969	36.5989	-3.2086***
	(9.3166)	(9.3112)	(9.1649)	(0.2308)
Export (EUR th.)	101684.5	111123.4	97670.48	-13579.15
	(414845.4)	(466469.6)	(390622.5)	(10419.68)
Export_intensity	0.4347	0.4368	0.4339	0.0031
	(0.2856)	(0.2917)	(0.2831)	(0.0072)
French_group	0.5236	0.5163	0.5264	0.0107
	(0.4995)	(0.4998)	(0.4994)	(0.0127)
Foreign_group	0.4684	0.4732	0.4667	-0.0072
	(0.4990)	(0.4994)	(0.4989)	(0.0127)
Leverage	1.2996	1.2685	1.3136	0.0441
	(2.2139)	(2.1908)	(2.2238)	(0.0556)

Source: EACEI, FARE, FICUS and The Annual Survey on the Resources Devoted to R&D Activities data. Standard deviations in parentheses. Information refers to the period 2005-2012.

Table 3.4: French firm's decision to start investing in eco-innovation (Probit estimations)

	Dependent variable: EnvR&D_d		
	(Model 1) (all firms) Probit	(Model 2) (polluters) Probit	(Model 3) (non-polluters) Probit
Pregrowthco2$_{i(t-1)}$	-0.0353	-0.0940	0.0522
	(2.7313)	(2.0457)	(3.8702)
Log_R&D$_{i(t-1)}$	0.0229	-0.0039	-0.0765
	(0.0571)	(0.0719)	(0.0841)
ExtR&D_d$_{i(t-1)}$	0.1668*	0.0683*	0.1052**
	(0.1187)	(0.0022)	(0.0023)
TFP$_{i(t-1)}$	0.4434**	0.0104*	0.1812 ***
	(0.1947)	(0.0052)	(0.0098)
Log_size$_{i(t-1)}$	-0.0661	-0.0005	-0.0055
	(0.0875)	(0.0015)	(0.0019)
Log_age$_{i(t-1)}$	-0.0708	-0.0034	-0.0043
	(0.0802)	(0.0018)	(0.0013)
Log_avewage$_{i(t-1)}$	0.1669	0.0042	0.0215*
	(0.3387)	(0.0099)	(0.0129)
Log_export$_{i(t-1)}$	-0.0051	0.0074	-0.0021
	(0.0255)	(0.0047)	(0.0039)
French_group$_{i(t-1)}$	-0.0287	0.0100*	0.0118**
	(0.4233)	(0.0059)	(0.0053)
Foreign_group$_{i(t-1)}$	-0.0165	0.0091 *	0.0117*
	(0.4276)	(0.0054)	(0.0064)
Leverage$_{i(t-1)}$	-0.0169	-0.0002	0.0003
	(0.0259)	(0.0004)	(0.0004)
log likelihood	-363.68	-275.05	-174.38
Wald chi2	131.43***	108.48***	98.53***
observations	711	218	509

Average marginal effects reported with standard errors in parentheses.
All regressions include sectoral, year and regional dummies.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.5: Effects of eco-innovation on firms' CO_2 intensity (system GMM estimates)

	Dependent variable: Co2_intensity		
	(Model 1) (all firms) GMM	(Model 2) (polluters) GMM	(Model 3) (non-polluters) GMM
Co2_intensity$_{i(t-1)}$	0.9702***	0.9873***	-0.2287
	(0.1206)	(0.0395)	(0.4094)
EnvR&D_intensity$_{i(t-1)}$	-0.5133	-3.0675	-0.1787
	(0.7239)	(2.3404)	(0.3043)
R&D_intensity$_{i(t-1)}$	-0.0205	0.1254	-0.1546*
	(0.0594)	(0.1319)	(0.0911)
ExtR&D_d$_{i(t-1)}$	0.0009	0.0001	0.0049*
	(0.0013)	(0.0026)	(0.0026)
TFP$_{i(t-1)}$	-0.0125	-0.0138	-0.0410*
	(0.0089)	(0.0189)	(0.0222)
Log_size$_{i(t-1)}$	-0.0029*	-0.0016	-0.0077*
	(0.0017)	(0.0034)	(0.0044)
Log_age$_{i(t-1)}$	-0.0012*	-0.0005	-0.0046**
	(0.0007)	(0.0027)	(0.0022)
Log_avewage$_{i(t-1)}$	0.0094	0.0094	0.0198
	(0.0092)	(0.0162)	(0.0180)
Export_intensity$_{i(t-1)}$	0.0004	-0.0018	-0.0015
	(0.0038)	(0.0051)	(0.0049)
French_group$_{i(t-1)}$	0.0041*	0.0014	0.0125
	(0.0025)	(0.0089)	(0.0083)
Foreign_group$_{i(t-1)}$	0.0029	0.0023	0.0131
	(0.0032)	(0.0075)	(0.0098)
Leverage$_{i(t-1)}$	-0.0001	0.0008	0.00001
	(0.0002)	(0.0008)	(0.0006)
AR(2) p value	0.822	0.212	0.365
Hansen p value	0.673	0.487	0.719
Observations	7,605	2,260	5,345
No.firms	1,867	538	1,329

Coefficients reported with robust standard errors in parentheses. All regressions include regional, sectoral and year dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.6: Balancing tests before and after matching for CO_2 intensity propensity score 1

Variable	Unmatched Matched	Mean Treated	Control	SD	Bias	t-test t	p¿t	V(T)/V(C)
Pregrowthco2	U	-0.00104	-0.0009	-0.4		-0.06	0.951	1.28
	M	-0.00024	-0.00112	3.8	-748.7	0.38	0.706	0.40
Log_R&D	U	7.0186	6.8483	9.8		1.61	0.107	0.85
	M	7.386	7.2818	6.1	38.4	0.61	0.542	0.89
ExtR&D_d	U	0.5342	0.5182	3.2		0.53	0.593	
	M	0.5824	0.5608	4.3	-35.3	0.42	0.678	
TFP	U	1.1452	1.2259	-21.2		-3.59	0.000	1.11
	M	1.0918	1.162	-18.5	13.0	-1.93	0.054	1.02
Log_age	U	3.1842	3.2274	-5.8		-0.97	0.330	1.10
	M	3.2699	3.2082	8.3	-44.1	0.80	0.424	0.80
Log_size	U	5.6121	5.3286	25.2		4.24	0.000	1.05
	M	5.8075	5.6725	12.1	52.1	1.20	0.230	1.07
Log_avewage	U	3.575	3.5504	10.4		1.71	0.087	0.85
	M	3.5961	3.5974	-0.5	94.8	-0.05	0.959	0.86
Log_export	U	9.3981	8.8601	19.1		3.15	0.002	0.88
	M	9.7308	9.5604	6.0	68.3	0.60	0.547	1.38
French_group	U	0.5457	0.5421	0.7		0.12	0.907	
	M	0.4890	0.4893	-0.1	91.0	-0.01	0.995	
Foreign_group	U	0.4413	0.4268	2.9		0.48	0.633	
	M	0.4945	0.5029	-1.7	41.2	-0.16	0.872	
Leverage	U	1.4095	1.4236	-0.6		-0.10	0.918	0.87
	M	1.1651	1.1723	-0.3	49.0	-0.03	0.977	0.46

Year, sector and region dummy variables not presented but included in the balancing tests. For these dummies, standardized differences (SD) are 0 and p-values of t-tests are 1 for the matched sample

Table 3.7: Balancing tests before and after matching for CO_2 intensity propensity score 2

Sample	Pseudo R^2	Likelihood Ratio Chi^2	p¿Chi^2	Mean Bias	Median Bias	B	R	%vAR
Unmatched	0.022	22.4	0.021	9.0	5.8	35.9	1.20	13
Matched	0.012	6.00	0.873	5.6	4.3	25.7	0.97	38

Table 3.8: Effects of eco-innovation on firms' CO_2 intensity (PSM-DiD estimates) with a bandwidth of 0.02

Treatment	(s=0)	(s=1)	(s=2)	(s=3)
Gaussian Kernel matching				
ATT	0.0015	0.0020	0.0078	0.0048
	(0.0024)	(0.0038)	(0.0053)	(0.0062)
N(T)	189	165	153	119
N(C)	581	580	580	471
Radius matching				
ATT	0.0031	0.0049	0.0079	0.0109
	(0.0031)	(0.0059)	(0.0066)	(0.0085)
N(T)	189	165	153	119
N(C)	581	580	580	471

Note: standard errors in parentheses. N(T) and N(C) are the numbers of observations for the treated and control groups respectively.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9: Effects of eco-innovation on firms' CO_2 intensity (PSM-DiD estimates with a bandwidth of 0.2*SD)

Treatment	(s=0)	(s=1)	(s=2)	(s=3)
Gaussian Kernel matching				
ATT	0.0014	0.0013	0.0089	0.0052
	(0.0025)	(0.0041)	(0.0057)	(0.0063)
N(T)	189	165	153	119
N(C)	581	580	580	471
Radius matching				
ATT	0.0048	0.0099	0.0169	0.0220
	(0.0067)	(0.0132)	(0.0139)	(0.0177)
N(T)	189	165	153	119
N(C)	581	580	580	471

Note: standard errors in parentheses. N(T) and N(C) are the numbers of observations for the treated and control groups respectively.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.10: Effects of eco-innovation on firms' CO_2 intensity by pollution intensity

Treatment	(s=0)	(s=1)	(s=2)	(s=3)
Pollution intensive				
ATT	0.0053	0.0091	0.0309	0.0239
	(0.0070)	(0.0127)	(0.0174)	(0.0195)
N(T)	58	48	44	32
N(C)	160	161	161	135
Non-pollution intensive				
ATT	0.00002	0.0004	-0.0016	0.0028
	(0.0018)	(0.0017)	0.0020	0.0047
N(T)	130	117	109	87
N(C)	413	411	411	332

Note: standard errors in parentheses. N(T) and N(C) are the numbers of observations for the treated and control groups respectively.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.11: Effects of eco-innovation on firms' fossil fuel intensity (system GMM estimates)

	Dependent variable: Fossilfuel_intensity		
	(Model 1) (all firms) GMM	(Model 2) (polluters) GMM	(Model 3) (non-polluters) GMM
Fossilfuel_intensity$_{i(t-1)}$	0.9562***	0.9852***	0.0345
	(0.1138)	(0.0431)	(0.2336)
EnvR&D_intensity$_{i(t-1)}$	-0.3869	-1.4139	-0.0082
	(0.4742)	(1.3150)	(0.0899)
R&D_intensity$_{i(t-1)}$	-0.0113	0.0729	-0.0473*
	(0.0275)	(0.0869)	(0.0304)
ExtR&D_d$_{i(t-1)}$	0.0004	-0.0008	0.0016**
	(0.0006)	(0.0012)	(0.0008)
TFP$_{i(t-1)}$	-0.0029	-0.0038	-0.0088
	(0.0044)	(0.0086)	(0.0061)
Log_size$_{i(t-1)}$	-0.0006	0.0002	-0.0019*
	(0.0009)	(0.0017)	(0.0012)
Log_age$_{i(t-1)}$	-0.0004	-0.0004	-0.0011*
	(0.0004)	(0.0017)	(0.0006)
Log_avewage$_{i(t-1)}$	0.0037	0.0031	0.0058
	(0.0044)	(0.0078)	(0.0059)
Export_intensity$_{i(t-1)}$	0.0002	-0.0007	-0.0013
	(0.0017)	(0.0029)	(0.0016)
French_group$_{i(t-1)}$	0.0018	-0.0003	0.0021
	(0.0014)	(0.0052)	(0.0018)
Foreign_group$_{i(t-1)}$	0.0013	0.0002	0.0009
	(0.0019)	(0.0042)	(0.0023)
Leverage$_{i(t-1)}$	-0.0001	0.0004	0.0001
	(0.0001)	(0.0005)	(0.0003)
AR(2) p value	0.834	0.722	0.577
Hansen p value	0.739	0.273	0.632
observations	7,612	2,260	5,352
No.firms	1,868	538	1,330

Coefficients reported with robust standard errors in parentheses. All regressions include regional, sectoral and year dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.12: Balancing tests before and after matching for fossil fuel intensity propensity score 1

Variable	Unmatched Matched	Mean Treated	Control	SD	Bias	t-test t	p¿t	V(T)/V(C)
Pregrowthfossilfuel	U	-0.00113	-0.0005	-5.1		-0.74	0.460	2.07
	M	-0.00024	-0.0011	5.3	-3.3	0.74	0.461	1.24
Log_R&D	U	7.0186	6.8495	9.8		1.61	0.107	0.85
	M	7.386	7.2867	5.8	41.3	0.58	0.560	0.90
ExtR&D_d	U	0.5342	0.5182	3.2		0.53	0.593	
	M	0.5824	0.5596	4.6	-43.1	0.44	0.661	
TFP	U	1.1452	1.2259	-21.2		-3.59	0.000	1.11
	M	1.0918	1.165	-19.2	9.5	-1.99	0.047	0.99
Log_age	U	3.1842	3.2274	-5.8		-0.97	0.330	1.10
	M	3.2699	3.218	7.0	-21.2	0.67	0.500	0.81
Log_size	U	5.6121	5.3304	25.2		4.24	0.000	1.05
	M	5.8075	5.6747	11.9	52.9	1.18	0.240	1.04
Log_avewage	U	3.575	3.5504	10.4		1.71	0.087	0.85
	M	3.5961	3.5984	-1	90.8	-0.09	0.927	0.87
Log_export	U	9.3981	8.86	19.1		3.15	0.002	0.88
	M	9.7308	9.5823	5.3	72.4	0.53	0.599	1.39
French_group	U	0.5457	0.5421	0.7		0.12	0.907	
	M	0.4890	0.4866	0.5	33.0	0.05	0.964	
Foreign_group	U	0.4413	0.4268	2.9		0.48	0.633	
	M	0.4945	0.5055	-2.2	23.8	-0.21	0.834	
Leverage	U	1.4095	1.4236	-0.6		-0.10	0.918	0.87
	M	1.1651	1.1973	-1.4	-127.7	-0.13	0.899	0.44

Year, sector and region dummy variables not presented but included in the balancing tests. For these dummies, standardized differences (SD) are 0 and p-values of t-tests are 1 for the matched sample

Table 3.13: Balancing tests before and after matching for fossil fuel intensity propensity score 2

Sample	Pseudo R^2	Likelihood Ratio Chi^2	p¿Chi^2	Mean Bias	Median Bias	B	R	%vAR
Unmatched	0.023	23.08	0.017	9.5	5.8	36.4	1.21	13
Matched	0.013	6.55	0.835	5.8	5.3	26.9	0.94	25

Table 3.14: Effects of eco-innovation on firms' fossil fuel intensity (PSM-DiD estimates)

Treatment	(s=0)	(s=1)	(s=2)	(s=3)
Gaussian Kernel matching				
ATT	0.0008	0.0058	0.0075	0.0095
	(0.0019)	(0.0067)	(0.0065)	(0.0097)
N(T)	189	165	153	119
N(C)	581	580	580	471
Radius matching				
ATT	0.0018	0.0109	0.0149	0.0173
	(0.0016)	(0.0113)	(0.0109)	(0.0164)
N(T)	189	165	153	119
N(C)	581	580	580	471

Note: standard errors in parentheses. N(T) and N(C) are the numbers of observations for the treated and control groups respectively.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.15: Effects of eco-innovation on firms' fossil fuel intensity by pollution intensity

Treatment	(s=0)	(s=1)	(s=2)	(s=3)
Pollution intensive				
ATT	0.0024	0.0225	0.0297	0.0362
	(0.0069)	(0.0228)	(0.0220)	(0.0358)
N(T)	58	48	44	32
N(C)	161	162	162	136
Non-pollution intensive				
ATT	0.0001	-0.0009	-0.0007	-0.0003
	(0.0007)	(0.0006)	0.0007	0.0008
N(T)	131	117	109	87
N(C)	420	418	418	335

Note: standard errors in parentheses. N(T) and N(C) are the numbers of observations for the treated and control groups respectively.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Conclusions, Limitations and Future Research

Main Findings and Policy Implications

In this thesis, we have presented three empirical studies to provide a deeper understanding of the various aspects of eco-innovation. Eco-innovation is a potential solution that provides a possible transition towards a cleaner, low carbon, and vibrant economy. During this transition, firms are key actors in the creation, adoption and diffusion of eco-innovations as well as the most important responsibilities for environmental protection. First, we examine the determinants of eco-innovation, particularly investigating the role of external R&D cooperation in stimulating eco-innovation. Using firm-level data focusing on French manufacturing firms over the period 2004 to 2011, we provide a comprehensive analysis of the characteristics favorable to eco-innovation. Our results suggest that external R&D cooperation leads to an increase in the level of investment in eco-innovation, more specifically, emphasizing the key role played by international R&D cooperation. Beside technological capabilities, we also highlight the importance of organizational capabilities and regulation stringency in promoting eco-innovation.

Second, we investigate the impact of environmental regulations on firm economic performance using a firm-level panel data of French manufacturing firms that invest in R&D. We test for the intermediate effect of regulation induced eco-innovation in offsetting environmental abatement pressure, known as the Porter hypothesis. Our results from an instrument variable approach show a negative and significant effect of environmental regulations on firm's productivity and regulation induced eco-innovation is not able to offset this effect. Among environmental abatement costs, end-of-pipe abatement costs reduce firms productivity significantly whereas integrated abatement cost does not. Regarding profitability, environmental regulations do not show significant effect on operating margin, however, regulation induced eco-innovation significantly reduces firms profitability. For both measurements of economic performance, firms in non-pollution intensive sectors are less sensitive to the change in regulatory stringency.

Finally, we examine the relationship between eco-innovation and firms environmental performance to assess the effectiveness of eco-innovation in reducing their environmental impact. Using a firm-level panel data on French manufacturing firms over the period 2005 to 2012, we measure environmental performance from two aspects, CO_2 emissions and energy structure. The results suggest that the decision to invest in eco-innovation does not significantly reduce neither carbon emissions nor fossil fuel usage. However, investing in general R&D does reduce the use of fossil fuel significantly. On the other hand, more productive firms in non pollution intensive sectors are more likely to reduce their fossil fuel intensity.

In addition, we analyse the change in CO_2 emissions intensity of French innovators that begin to invest in eco-innovation, we find that relative to a control group, the CO_2 emissions intensity of new eco-innovators is not statistically different in the year when they start investing in eco-innovation. The treatment effect remains insignificant in the next three years. Furthermore, we find that CO_2 emissions intensity is not significantly reduced after they decide to invest in eco-innovation for both pollution intensive firms and non pollution intensive firms. Similar treatment effects of eco-innovation on fossil fuel intensity are observed.

To conclude, the empirical results in this thesis have important policy implications on the possible ways to achieve the sustainable targets for firms and policymakers. First, the results suggest a substantial role for external knowledge sourcing, especially international R&D cooperation in stimulating eco-innovation. This significant effect of R&D cooperation indicates the presence of technological inter-dependencies on knowledge and resources. At the development stage of eco-innovation, firms are able to share costs and risks through R&D cooperation. Thus, R&D cooperation requires more efficient public support in the search for external knowledge sources by improving cooperation networks and firms R&D patterns, in order to reduce the coordination costs that curb R&D cooperation. Second, from our analysis of the effectiveness of eco-innovation, and its impact on firm performance, well designed environmental regulations are essential. The actual policy mix needs to be complex and dynamic, to reach a win-win situation and well designed environmental policies should include a combination of different policy instruments. Hence, government policies targeting on boosting eco-innovations need to be supported by correctly aligned regulatory frameworks which comprise various market-based instruments for pollution abatement. Overall, with the presence of sector heterogeneity, eco-innovation requires more support from well designed and targeted environmental regulations which would provide incentives to firms to engage in eco-innovation by using a mixture of various market-based instruments.

Limitations

Although the empirical results presented in this thesis have been subject to a number of robustness checks, our study sill suffers from several potential limitations. One of the potential concerns arises from the data used to perform the empirical analysis. For instance, although the R&D data used in chapters provides a good representation of the innovation activities carried out by French firms, unfortunately it is only available for a relatively small group of French innovators, offering complete coverage of large innovators but only a partial representation of firms investing less than 350,000 Euros which are randomly surveyed every year. Also, the R&D data provides detailed information on the environment related R&D within internal R&D investment, whereas the decomposition of external R&D cooperation is not available. Furthermore, another limitation of the data regards the time period. The relatively short period of the panel data causes some concerns regarding the generalisability of the findings.

Moreover, another concern arises from the absence of consideration of knowledge spillover effect. R&D is different from other inputs that the amount of R&D spent in one firm can have spillover effects on other firms in the same industry, firms in other industries and both within the domestic economy (domestic spillovers) and abroad (foreign spillover). Hence, while measuring the returns to R&D one needs to consolidate the benefits that flow through these different channels. Without considering the R&D spillover effect, our results may suffer from the omitted variable bias.

Also, another limitation comes from the way we calculate the CO_2 emissions intensity. Since we generate the CO_2 emissions intensity by multiplying each fuel consumption type by an emissions converter, this variable only provides limited information on carbon emissions instead of all other types of pollutants emitted during the production process. However, eco-innovation may not be only focusing on reducing carbon emissions. This could potentially under estimate the effect of eco-innovation on environmental protection.

Another concern arises from the estimation methodology applied in this thesis due to the issue of endogeneity which could potentially affect our results. For example, we have discussed the lobby effect on environmental regulation which may cause inherent bias. Pressure from anti-environmental lobbies could make policymakers reluctant to implement more stringent environmental policies that could protect the environment and result in economic benefits. The endogenous political decisions could potentially weaken our results. Also, since we only innovators are considered in our empirical analysis, another endogeneity concern comes from the selection bias in which the firms invested in eco-innovation are endogenously different from those which have not been investing in innovation at all.

In this thesis, we have implemented a number of econometric techniques to account for different endogeneity concerns and we have demonstrated the robustness of our results using a number of alternative approaches. We hope that through implementation of various econometric techniques, our results reflect the actual effect of eco-innovation. However our analysis might still be affected by different sources of bias which are difficult to address.

Future Research

The results of this thesis provide some empirical evidence on eco-innovation, and can be extended in a number of ways. First, besides using input measures such as environmental R&D expenditure for eco-innovation, it would be interesting to consider output measures such as the number of green patents or descriptions of ongoing individual innovations. Output measures for eco-innovation explicitly give an indication of intellectual output can be used to measure research activities and to study the direction of research in a given technological field. Combining input and output measures at the same time could identify to what extent R&D investment can be transformed to successful patents which could bring a more comprehensive understanding of eco-innovation.

Second, to investigate the effect of eco-innovation on firm performance would not be complete without a comprehensive indication of government regulations. In this thesis, we use environment abatement costs to measure regulation stringency and it would be interesting to bring in more elements reflecting the enforcement of environmental regulations, for example, the number of inspections from environmental agency. An extensive study might be needed to evaluate the relationship between joint effect of regulation enforcement and regulation compliance on eco-innovation.

Third, this thesis has partially addressed the influence of international trade by considering export activities, it might be interesting to further investigate the relationship between eco-innovation and other aspects of firms internationalization strategy. The link between eco-innovation and trade patterns instead has been mostly neglected in the literature especially at the firms level, probably due to the lack of data availability. Such a study might be particularly useful in enhancing our understanding on how do firms shift their trade patterns to cope with eco-innovation strategies.

Last by not least, it would be interesting to decompose public R&D funding into different aspects. In this thesis, we do not find evidence supporting the impact of pubic funding on eco-innovation. The French public sector invests significant public resources to R&D activities every year, and benefit from advanced high-tech industries, pro-active government policies and high quality research institutions. It would be particularly useful to evaluate the effectiveness of dis-aggregated public support in enhancing eco-innovation development, in terms of the output of R&D activities supported by public authorities targeting on environmental protection.

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